What information makes airborne lead pollution salient to homeowners and who does it cost? Evidence from US airports

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Abstract

While the US Environmental Protection Agency phased out use of leaded gasoline prior to the year 2000, an exemption for aviation gasoline remains in place to date. Leaded aviation gasoline's use is widespread – around 500,000 gallons/day in the US – and its pollution is centralized at thousands of airports. Starting from the premise that noise pollution is the salient disamenity associated with residing near airports, I study how information shocks about the risks from leaded avgas affect housing prices in the vicinity of over 1000 US general aviation airports. I find little evidence that local prices respond to (i) substantial changes in EPA ambient lead standards, (ii) revisions to airport air quality monitoring requirements, (iii) litigation-mandated local disclosure letters, or (iv) variations in local lead emission levels from aviation traffic. I do find strong initial price responses following reported violations of ambient lead standards, consistent with an immediate, short-run change in risk perceptions. I tie these findings to the environmental justice literature by studying neighborhood demographic compositions in lower- and higher-information time periods. When less information about lead risk is available, I find that neighborhoods within 1000m of an airport, especially those downwind, have higher percentages of minority inhabitants, lower median incomes, and a less educated populace. Following the release of new information, demographic changes align with a sorting narrative: neighborhoods within 1km of an airport in violation of ambient lead standards see a decline in the population of children under age ten, a shift in racial demographics, and a fall in median income.

Keywords: information, leaded gasoline, air pollution, salience, airport, environmental justice

JEL Codes: Q5, D9, R2

1 Introduction

Economists have long viewed the provision of up-to-date and unbiased pollutant information as an essential component of environmental policy. In the absence of complete information about emission levels and toxicity, individuals' decisions on matters such as where to live may be sub-optimal. In this paper, I add to a growing body of research that examines consumer responses to environmental information shocks. In particular, I study price responses in local housing markets

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during a series of information disclosures pertaining to potential airborne lead risk at general aviation facilities in the United States. I then evaluate these results in the context of recent theoretical work showing that missing or incorrect pollution information can worsen issues of environmental injustice (Hausman and Stolper, 2020), and argue that "hidden pollution" is likely present in airport-proximate neighborhoods due to noise being the salient local disamenity.

Often cited as a cornerstone success story of US environmental policy, regulation from the Environmental Protection Agency (EPA) targeting leaded automotive gasoline reduced average airborne lead concentrations in the US by a factor of over ten between 1980 and 2010. Despite this broad and dispersed reduction, localized airborne lead pollution remains common in some areas. Industrial manufacturing, electricity generation, smelting, and refining are well-known and visually apparent sources of such pollution. But following the adoption of more stringent industrial air quality standards in the mid-2000s, aviation gasoline is by far the largest remaining source of ambient lead in the US.

General aviation airports are network hubs for lead-emitting aircraft. According to data from the 2008 National Emissions Inventory, localized lead emissions at these facilities accounted for 58% of annual airborne lead in the US (EPA, 2014). Research in public health, engineering, and transportation studies have demonstrated that well-trafficked airports and their downwind vicinity act as lead hotspots. Scientific evidence has also linked elevated blood lead levels with close residential proximity to an airport. Elevated blood lead levels are associated with a bevy of developmental problems in children, as well as cardiovascular and reproductive issues in adults. If potential homebuyers are aware of these risks to children and themselves, neoclassical economic theory suggests that expected current and future exposure levels from a nearby lead pollution source should capitalize into a property's sale price.

Evidence on homebuyers' attentiveness towards environmental information is mixed, however. In research studying housing market responses to the publication of Toxic Release Inventories (TRIs), perhaps the most comparable form of environmental information disclosure to those I consider here, some papers find strong price effects (Mastromonaco, 2015; Moulton et al, 2018), while others do not (Bui and Mayer, 2003; von Graevenitz et al, 2018). A similarly varied set of sales price results exist following inclusion or delisting of local Superfund sites (Gayer et al, 2000; Greenstone and Gallagher, 2008; Gamper-Rabindran and Timmins, 2013).

In the face of this mixed set of evidence, my paper adds a case study to the literature by empirically testing the limits of property market capitalization following varied information releases concerning emissions and potential health hazards. I study a series of events from 2008 to 2015, including federal policy revisions, air quality monitoring releases, and a litigation-mandated local information disclosure. This evolving information environment provides a set of natural experiments that can test the degree to which housing markets in close proximity to airports viewed potential exposure to elevated lead emissions as a salient local attribute. I frame these information environments along two characteristic spectra – public/private and generic/specific – and show empirically that specific, public information is strongly capitalized in the short-run, while more generic or privately-held information does not move housing markets.

Using several variations on a distance-gradient-based difference-in-differences identification strategy (Currie et al, 2015; Haninger et al, 2017; Taylor et al, 2016), I find a large but fleeting price response following the initial release of airport-level ambient lead monitoring results – a location-specific, public information event in 2013. At facilities found to be in violation, sales prices within 1km drop roughly 30% in initial months, tapering off to an average 10% decline over the full course of the first year. Similar research designs built around two information events that were also public but less specific in nature – an order-of-magnitude reduction to the EPA's ambient lead standard in 2008, and a 2009 federal policy revision mandating air quality monitoring at high-lead-emission facilities – uncover no local price responses. Lastly, I find that private information provision about airport-generated lead pollution from litigation-generated local disclosure letters in 2015 also had null effects on property markets.

In aggregate, I take this body of results as a strong signal that air pollution is rarely a local feature that homebuyers note while considering a purchase near airports. Appealing to theory described in Bordalo, Gennaoli, and Schleifer (2013), I posit that *noise* pollution is typically the salient local attribute of these properties. This results in a relative underweighting of potential lead exposure in homebuyers' decision calculus when compared to property purchases with other, more salient sources of lead exposure.[1] My empirical results suggest that lead pollution only becomes salient in this context when an airport falls into noncompliance with federal ambient lead standards.

In the final section of the paper, I examine environmental justice outcomes in this pollution and information setting. This setting is opportune for empirically testing theoretical propositions from Hausman and Stolper (2020). Their paper argues that when households are underinformed (even uniformly) about potential health damages from pollution and sort based on income and more salient but pollution-correlated local disamenities (like airport noise), low-income households will dispropotionately suffer from pollution exposure and excess welfare losses. The welfare implications of this information-centric narrative has added appeal in the context of lead, which is largely a legacy pollutant that predominantly remains in poorer environs.

First, I test whether poorer households or those headed by racial/ethnic minorities suffer disproportionate exposure to "hidden" air pollution during the five years prior to EPA airport-level monitoring. In contrast to a recent EPA report (2020) finding no national disparities in exposure to avgas-generated lead by race or income, my descriptive analysis using within-airport variation finds evidence that neighborhoods directly downwind of general aviation facilities have relatively higher percentages of minority inhabitants, lower median incomes, and a less educated populace. Second, I study how neighborhoods' compositions change in the five years following the EPA's release of their lead monitoring results at 17 airports. Though these results rely on a fairly small sample size, I observe demographic changes that align with environmental sorting: neighborhoods within

[1]Several recent papers have provided evidence that discrete changes in lead exposure from paint and plumbing do capitalize into home values (Billings and Schnepel, 2017; Theising, 2019; Christensen et al, 2019). Others have shown that information releases or policy mandates about potential lead exposure generate property market effects (Christensen et al, 2019; Mastromonaco, 2015; Gazze, 2020).

1km of an airport in violation of ambient lead standards see a decline in the population of children under age ten, a shift in racial demographics, and a fall in median income. While these patterns are more suggestive than causal, they are consistent with the "coming to the nuisance" narrative.

The remainder of the paper is as follows: the next section discusses background information on the health risks of lead and details the ongoing use of lead in aviation gasoline. Section 3 describes the data used in this paper. Section 4 examines how local property markets respond to new information about potential lead exposure near general aviation airports. Section 5 studies the sociodemographic characteristics of households who live close to these airports, looking for evidence of environmental injustice patterns. Section 6 concludes.

2 Scientific and policy background information

Consumption of lead has serious health repercussions for all humans[2], but especially for children and pregnant women. Exposure has been shown to decrease fecundity and fertility in both men and women, and lead consumption by pregnant mothers is associated with increased rates of fetal mortality and infant health complications.[3] After birth, exposure is associated with developmental problems in infants and children, including diminished IQ, hyperactivity or behavioral problems, and delayed physical growth. These effects can compound through childhood in the fashion described by Currie et al (2014): lead exposure in a child's early years has been linked with poor educational outcomes, propensity for delinquency and crime, and diminished lifetime socioeconomic status.[4]

Today, lead is mostly a legacy problem in the US. The most common sources of modern human contact include lead paint and/or piping in older homes and workplaces, remnants in dust or soil that are naturally occurring or from previous lead emissions, and current emissions from industrial or mechanical sources. Notably, while the use of lead has been banned or restricted from several of these sources – namely, paint (1978), plumbing (1986), and automotive gasoline (1996) – the use of leaded aviation gasoline remains unrestricted in the US.

Aviation gasoline (avgas) is used by piston-fired plane engines. Inclusion of tetraethyl lead in the gasoline compound prevents engine knock and potentially catastrophic engine failure. Piston engine aircrafts (PEA) are common in US aviation and typically seat 1-12 passengers, making relatively short trips covering distances of under 500 miles. In 2015, they accounted for just over two-thirds of the general aviation fleet in the US (GAMA, 2016). Despite some PEAs' ability to fly on non-ethanol unleaded automobile gasoline (mogas), avgas remains the standard gasoline on offer at general aviation airports across the country, with only a handful offering the mogas alternative (Kessler, 2013).

[2] See Kosnett et al, 2007 and Lanphear et al, 2018 for recent summaries of health impacts resulting from adult exposure.

[3] See NTP, 2012; Clay et al, 2014; Clay et al, 2018; Grossman and Slusky, 2019.

[4] See, amongst many others in this rapidly expanding literature: Rau et al, 2015; Reyes, 2015; Reuben et al, 2017; Aizer et al, 2018; Gronqvist et al, 2020.

Following the EPA's 2008 downward revision of the national ambient lead standard from $1.5\mu g/m^3$ to $0.15\mu g/m^3$, several parties in environmental policy circles speculated on the potential for airports with heavy PEA traffic to be in exceedance of this level. Monitoring at several airports has since confirmed this to be the case: an EPA study of 3-month average airborne lead concentrations at 17 general aviation airports across the US found two airports in exceedance of the standard (EPA, 2013). In addition, dispersion modeling and soil testing have confirmed the existence of lead hotspots at airports with heavy PEA traffic. Dispersion models used by Feinberg and Turner (2013) and Feinberg et al (2016) show airborne hotspots in run-up, taxiing and takeoff areas, while Carr et al (2011) find elevated air and soil lead concentration gradients up to 900m downwind of the airport. McCumber and Strevett (2017) show increased soil lead concentrations downwind of airport activity areas, particularly fueling stations.

This set of evidence can be further analyzed in light of three recent academic papers showing a robust dose-responsive relationship between proximity to PEA traffic and blood lead level (BLL) in children and adults. Using data from six counties in North Carolina, Miranda et al (2011) find a well-powered correlation between a child's BLL and their distance to an airport. The authors measure BLL continuously and find that children residing close to airports have average BLL levels that are 3-5% higher than baseline. The strongest effects are within 500m, though significant effects remain consistently out to a distance of a kilometer. Expanding on their research design and better controlling for confounding factors such lead paint, point source polluters and wind direction, Zahran et al (2017) use data from Michigan to elicit evidence of a relationship out to distances of 3km.[5] The paper also makes use of an exogenous shock - reduced piston engine traffic in the months following the terrorist attacks of 9/11 - to causally demonstrate a reduction in average child BLL during periods of decreased aviation traffic.[6] Finally, Park et al (2013) study BLLs of aircraft maintenance crews across airports in South Korea. Controlling for individual and lifestyle characteristics, the authors find elevated BLLs for crew members who work closer to the runway at airports using leaded gasoline.

Despite this wide-ranging support for a scientific link between airport proximity and elevated BLLs, the EPA – as of date – has declined to make an official endangerment finding about leaded avgas. While joint efforts between the EPA and Federal Aviation Administration (FAA) are aiming to find a suitable universal fuel replacement for avgas, an endangerment finding would dramatically speed up the timeline and likely engender immediate restrictions on leaded avgas similar to those restrictions on paint, pipes or auto gasoline. In the meantime, proactive pilots and airports have been stuck with the costs of certifying their plane as mogas-safe or providing an alternative fuel.[7]

[5] Compared to children living more than 4km from an airport, the authors find that children living within one kilometer of an airport are 25.2% more to possess a BLL above the $5\mu g/dL$ current Centers for Disease Control (CDC) threshold and 44.9% more likely to possess a BLL above the $10\mu g/dL$ threshold previously held by the CDC.

[6] Though not directly related to lead emissions from avgas, recent quasi-experimental research by Hollingsworth and Rudik (2021) also finds evidence of decreased BLLs at even larger distances following NASCAR's switch to unleaded auto racing fuel in the mid-2000s.

[7] The FAA mandates additional compliance in order for PEAs to run on unleaded fuel- the cost of this supplemental fuel-type certification runs into the thousands of dollars. Airports can also face infrastructure costs into the tens of thousands of dollars when retrofitting their fuel provision systems.

Given these costs, private uptake of these alternative technologies has been relatively muted. In the absence of a universal fuel alternative or shift in federal policy, avgas seems likely to remain the standard into the immediate future.

3 Data materials

In this section, I describe data used to undertake the analyses that follow. All data mentioned is publicly available, except Zillow's ZTRAX product.[8]

Airport location and emissions: My primary research goal is understanding how information shocks impact localities near airports with avgas-generated lead pollution. Though there are nearly 20,000 US public-use airports registered via the FAA's Form 5010, I focus my attention on a subset of general aviation airports with substantial PEA traffic.

My airport inclusion criterion is ultimately based on the EPA's Toxic Release Inventory (TRI) lead reporting threshold. Industrial facilities are required to annually report any manufacturing, processing, or other activity that uses more than 100 pounds (0.05 tons) of lead. Though airports are not industrial and therefore not obligated to report lead byproducts under these Right-to-Know regulations, many do have sufficient annual PEA traffic to produce emissions that exceed the reporting threshold. Given the need for an inclusion standard and the information-based similarites between the TRI and my study, I elect to restrict my airport sample to all US airports with at least 0.05 tons of reported lead emissions in 2008. I procure estimates of airports' 2008 lead emissions from the EPA's point source National Emissions Inventory. When merged with FAA's database, which provides general information about the airport including location, runway bearings, and gasoline types offered for sale, I am left with a baseline sample of 1,326 airports scattered across the US's 50 states and the District of Columbia.

Because my analyses are spatial in nature, I require a matching airport shapefile. I draw this shapefile from three sources. The primary source is the "North America Airports" boundary shapefile produced by ESRI. For airports not included in this base shapefile, I supplement the data by including user-drawn boundaries from an OpenStreetMaps API. Finally, for the small number of airports still missing boundaries, I simply impute the airport's longitude and latitude as reported in the FAA 5010 database.

Real estate sales transactions: To measure consumer perception of lead risk from avgas emissions, I will study the evolution of housing prices over time. Economists have long engaged real estate markets to study the implicit valuation of local public (dis)amenities. Real estate transactions have proven a sensible barometer of amenity value for several reasons: the immovable and fixed supply of land, the typically consequential financial nature of a property transaction, the widespread availability of data, and a flexible set of econometric tools capable of answering varied questions.

[8]Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTrax). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author and do not reflect the position of Zillow Group.

I rely on transaction and assessor real estate data from the October 2020 version of the ZTRAX database. My analyses include transactions occurring between October 2007 and March 2016. I omit non-arms-length sales based on deed type and the database's inter-family flag, and further constrain my sample by excluding transactions on multi-family properties and those with non-residential land uses. To follow best practices and remain conservative in analysis (Bishop et al, 2020), I drop transactions with a sales price of less than $10,000 or more than $10 million.

To ensure a broad geographic coverage while maintaining an ability to consistently control for property-level characteristics, I ultimately extracted the following variables from the database: sales price, date of sale, age of home, total bedrooms, total bathrooms, and the property's lot size. Using each property's latitude and longitude coordinates, I calculate two additional geographic measures. The first is a measure of the minimum distance (in kilometers) from the property to its nearest airport's spatial boundaries. I use this distance measure to restrict the study sample to only properties within 5 km of a relevant airport.[9] The second is a compass bearing from the centroid of the airport to the property in question. This latter measure is used to assign wind frequency and flight paths to each property.

Lastly, Zillow procures its raw data from county assessor and recorder offices. In some US states, recorded documentation of property transactions are not required to disclose sales price. Given that ZTRAX's coverage of transactions with recorded prices are exceptionally sparse in these 11 states – and that those including such information are likely highly selected – I elect to omit all transactions falling in non-disclosure states from my price analyses.[10]

American Community Survey (ACS) data: I am also interested in the demographic composition of neighborhoods in proximity to airports during the study period. I obtain this information at a fairly high spatial resolution by incorporating 5-year ACS block group data on income, housing status, education level, and race. I rely on measures from the 2009-2013 and 2014-2018 samples. Using sample-consistent block group shapefiles from the 2010 Census, I again create measures of neighborhood distance and compass bearing using the block group's centroid. Because my statistical analysis in Section 5 relies solely on within-airport distance variation, I elect to omit all observations from airports where fewer than five census block groups fall within 5km of the airport boundary. As such, my ACS-based results in that section are representative for fairly population-dense areas; I cannot say much about how my findings in this section hold for the roughly 300 airports in more rural areas where block group geographies span broader areas.

Flight data: In some heterogeneity analyses, I examine differential effects based on airport traffic levels. Data on flight activity comes from the FAA's Traffic Flow Management System. This database collects information from registered flight plans and automated detection on the National Aviation System for several thousand airports in the US. I extract annual airport-level flight operation counts for PEAs and separately for all aircraft.[11]

[9]If the resulting set of transactions for an airport is smaller than 100 for the entire study period, I drop the airport from my sales sample due to thin markets. This happens for a small number of airports in rural areas.

[10]These states are: Alaska, Idaho, Kansas, Louisiana, Mississippi, Montana, New Mexico, North Dakota, Texas, Utah, and Wyoming.

[11]PEA are small aircraft that often fly at lower altitudes. Due to how the TFMS captures air traffic, it is possible

Wind data: I procure airport-level historic wind data from windhistory.com. The measures I use from this website include wind direction counts and average speeds for each 10 degree tranche of the compass rose during the period 2006-2010. The raw weather observations used to create the website's cleaner measures come from NOAA's METAR database. This raw data is not collected regularly at the smallest public and private airports, so I lack wind measures in those cases. I aggregate the website's direction counts and wind speeds from the 10 degree level up to compass octants (N,NE,E,SE,S,SW,W,NW) to reduce noise, then assign properties and census block groups wind frequency and intensity measures based on their compass bearing relative to the airport.

In summary: This section concludes with references to summary statistics and figures describing the final study samples and database. Figure 1 maps the national spatial coverage of 1,326 airports with Pb emissions levels exceeding 0.05 tons in 2008, and indicates those included in my sales analysis. A set of detailed summary statistics describing sales transaction and block-group-level demographics for a representative airport – Zamperini Field in Torrance, CA – are available in Appendix Table A1 and Table A2. These transactions and block groups are also visualized for Zamperini Field in Figure 2 and Figure 3; as I now transition into describing my research design, these figures should provide a sense of the within-airport spatial variation I rely on to identify parameters of interest.

4 Property value capitalization of environmental information

In this section, I describe a series of regulatory and legal information releases pertinent to lead-emitting airports, and employ a research design that detects whether local property markets were affected by these information shocks. These events occurred between October 2008 and March 2015; in Figure 4, I illustrate an overview of this timeline and the respective event windows studied. To maintain a clear narrative in what follows, I work through the four events chronologically, rather than thematically. Nevertheless, this section's intended thematic take-away is that differing classes of information provision on the same general subject result in varied short-run housing market outcomes.

Firming up ideas simply, let information on local environmental quality be characterized along two dimensions: public versus private and generic versus specific. The textbook neoclassical theory underlying efficient housing markets and hedonic pricing assume all relevant information is public and therefore fully captured by the price mechanism. A shift from private to public information reduces information asymmetries, and is the motivating theory behind mandatory disclosures (Grossman, 1981; Chau and Choy, 2011). Information can also be generic or specific in nature: for example, the former type could be of the form "this chemical is toxic" while the latter may read like "this chemical is toxic and present at the following set of products...". In essence, a specific piece of information may be more directly actionable to the information receiver.[12] In alignment

that this data systematically undercounts PEA flights. To my knowledge, no better source of similar data exists for PEA traffic counts. For more details on measurement: https://aspm.faa.gov/aspmhelp/index/TFMSC.html

[12] A distinct but vaguely related dimension of information is coarseness versus complexity (Houde, 2018). For

with this simple, two-dimensional economic and behavioral framework, I will find strong housing market capitalization of information about airborne lead at airports when provision is public and specific in nature. When information is released privately or is more generic in nature, housing markets do not respond.

The next subsection describes my empirical strategy. Subsections 2-5 highlight results from each of the four information events I study. Subsection 6 summarizes the robustness of my findings.

4.1 Empirical strategy

To detect information-driven deviations in local housing prices, I turn to variations on a simple difference-in-differences econometric framework; within these variations, I examine potential heterogeneities in price response. In each case, I study event windows spanning 365 days before and after an information release. Thus, I am implicitly looking for short run differential price effects. While the tools I rely on for econometric identification of information capitalization are derived from the quasi-experimental literature, the underlying methodology of my research design is also grounded in traditional hedonics (Parmeter and Pope, 2013).

To be clear, however, the empirical exercise undertaken here is reduced-form in nature. I do not formally disentangle separate marginal prices for co-located airport (dis)amenities like air quality and noise. Instead, through the lens of home prices, I simply study whether or not newly released information renders poor air quality more salient to local residents. Thus, I assume *a priori* that potential airborne lead does not fall within the spectrum of property markets' awareness before these information releases.[13]

The baseline empirical specification is of the form:

$$\log(Price)_{ijst} = \alpha_j + \beta \text{Dist}_i + \gamma \text{Post}_t + \delta \text{Dist}_i \times \text{Post}_t + \tau_t + \eta_s \times t + \rho_j X_i + \varepsilon_{ijst} \tag{1}$$

A log-linear functional form is assumed to ease price comparisons across airports, with i indexing individual properties, j indexing airports, s denoting states, and t marking a point in time. In all related models that follow, denote $t = 0$ on the day of information release. My treatment variable in this diff-in-diff framework is distance-related. Dist_i is a set of indicator variables, differentiating properties by distance-to-airport bandwidths: those within 1km, those between 1-3km away, and the base group located 3-5km away. The choice of distance bandwidths is arbitrary, but follows the literature in allowing capitalization of point-source-derived environmental disamenities to taper off with distance (Currie et al, 2015; Taylor et al, 2016; Mastromonaco, 2015). Post_t is an indicator variable for all property transactions occurring after the information release ($t > 0$). δ, the parameters for the interactions of Dist_i and Post_t is my estimate of interest.

The model includes calendar month fixed effects (τ_t) to capture the seasonality of housing prices,

example, a coarse information signal (i.e. pass/fail, efficient/inefficient) simplifies underlying complexity of a product's quality. This dimension may well apply to information about air quality (NAAQS thresholds/violations, AQI bins, etc.) but is not what I focus on here.

[13]Indeed, my results from section 4.6 lend some support to this assumption.

state-varying time trends ($\eta_s \times t$) to accommodate different regional housing market patterns, and airport-specific intercepts (α_j). In models where I include housing structure control variables (X_i: lot size, (lot size)^2 age of home, (age of home)^2, bedrooms, bathrooms, and an indicator for whether the property is directly under a flight path), I allow (linear) marginal prices (ρ_j) for each characteristic to vary by airport, in essence modeling separate structural hedonic functions for each locale. To be clear, while I rely on within-airport distance variation to identify δ, I do not allow it to vary by airport; thus my estimate of these parameters is a simple national average of a distance-differentiated information capitalization effect in the year following a release. For all results in this section, I cluster standard errors at the airport level.

The principle assumption required for a well identified estimate in this framework is common price trends across distance bandwidths after controlling for differences in housing quality, season of sale, and differential trends across states. The prospect of common trends holding in this case seems reasonable, given that we consider only properties in a relatively tight neighborhood (5km) surrounding airports. In addition to these baseline difference-in-differences models, I estimate triple difference models that are of keener interest. For each event studied in the following subsections, there are reasons to expect differential treatment responses to information. I discuss these triple difference variations in turn below, and provide evidence in support of common pre-trends for each.

4.2 Event 1: 2008 revision to lead NAAQS

I now turn to the first information event. To set the stage, it's useful to note that US regulation of ambient lead began in 1978. In response to lead's increasingly apparent danger as a widespread air pollutant, a NAAQS for total suspended lead particulate was set at 1.5μg/m^3. Generally speaking, as leaded automobile emissions fell from the 1970s-2000s, ambient levels did as well - in early 2008, only two US areas (East Helena, MT and Herculaneum, MO) were not in compliance with the 1978 standard. This 1.5μg/m^3 standard remained in place and unchallenged until 2004, when a lawsuit by an environmental group in Missouri, directed at the EPA's negligence in reviewing the lead NAAQS since 1978, resulted in a consent decree mandating review of the standard by 2008.[14]

The fallout of this litigation produces an information shock in October of 2008. At this time, the EPA finalized its decision on an updated standard (73 FR 66964). Effective as of 2009, the primary lead NAAQS would be set at 0.15 μg/m^3 - a reduction of an order of magnitude. This substantial regulatory change discretely signaled an update to the EPA's scientific view on the safe level of ambient lead exposure. Many lead emitting facilities – including airports – previously well in compliance with federal air quality regulations, were suddenly above or close to the national standard.

My first set of regression results investigates whether property markets close to lead-emitting airports responded to this new information. To emphasize: this NAAQS revision was the EPA's first update to airborne lead policy in thirty years, and under full information provision, the size of

[14]The Clean Air Act requires the EPA to review NAAQS every five years. Litigation and follow-up documentation is available here: https://www.epa.gov/naaqs/lead-pb-air-quality-standards-documents-review-completed-2008

the change should provide households with an obvious and up-to-date understanding of the health dangers associated with lead exposure. Of course, whether households note such federal policy changes is context-dependent, and is what I seek to determine here.

I present my baseline diff-in-diff results in columns (1) and (2) of Table 1. For completeness, I include specifications both with and without housing-structure controls.[15] As expected, results show that properties closer to the airport sell at a discount on average, both before and after the information release. This discount is stronger for properties within 1km of the facility, but exists out to a distance of 3km, confirming that the research design does capture some disamenity value of airports. Speaking generally, I find this result to hold across all events and specifications, so will not highlight it further.

My diff-in-diff interaction parameters are more mixed in interpretability. In the preferred specification shown in column (2), for the properties in closest proximity to an airport, I find a small but statistically significant decline in prices. One potential threat to interpreting this as a pure capitalization effect would be the existence of confounding events near the time of information treatment that could differentially affect pricing by distance to airport. In this particular case, one can note that my event window occurs in the midst of the 2008 financial housing crisis. It is entirely conceivable that the real estate market's collapse could generate sharper price declines in neighborhoods very close to noisy airports.

To dig into this potential confounding factor, I estimate a triple difference model that seeks to differentiate the price effect based on perceived pollution exposure intensity. I subdivide airports into quartile groups by the fraction of their aviation traffic coming from PEAs. Creating a set of indicator variables for each quartile (Quart_j), I then interact these indicators with the diff-in-diff interaction in Equation (1):

$$\begin{aligned}\log(Price)_{ijst} = \beta_1 \text{Dist}_i + \beta_2 \text{Dist}_i \times \text{Quart}_j + \gamma_1 \text{Post}_t + \gamma_2 \text{Post}_t \times \text{Quart}_j + \\ \gamma_3 \text{Post}_t \times \text{Dist}_i + \delta \text{Dist}_i \times \text{Post}_t \times \text{Quart}_j + \text{FE}_{\alpha,\tau,\eta} + \rho_j X_i + \varepsilon_{ijst}\end{aligned} \tag{1.1}$$

This triple difference model allows me to see whether the post-information-release price effect varies by local PEA frequency. If the capitalization effect is indeed driven by the NAAQS revision rather than concurrent economic forces, one should expect a stronger decline at airports where PEA traffic is a larger portion of local flights.

The results from this specification are presented in columns (3) and (4) of Table 1. Summing point estimates in these columns, I find little evidence of heterogeneity that could lend support for the pure information capitalization effect driving stronger price declines near airports. For households within 1km of an airport, post-treatment price decreases are largest for the bottom and 2nd quartile - those airports with lower rates of PEA traffic. Put another way, airports in these quartiles are likely to be larger, commercial aviation facilities, with higher rates of jet traffic and

[15] My preferred estimates include these controls to account for potentially differing housing structure compositions across distance groups. However, 25-30% of sample-eligible airports are in counties where Zillow does not have this set of complete information, so I share both sets of results to allay any selection-related concerns. As shown, none of my results differ wildly based on this distinction.

very few PEA flights. In any case, group differences in estimated heterogeneity are economically small, and not statistically significant. I supplement the parametric estimation of Equation (1.1) with a non-parametric event study in Figure 5. With an identical estimation sample, I use a local polynomial estimator (Fan and Gijbels, 1996; Haninger et al (2017); Guignet et al (2018)) on residuals of log($price$) after conditioning on airport and month fixed effects, state-specific time trends, and housing structure characteristics. I fit the estimator separately for each quartile and distance bin, and allow for a break in respective residual price functions at $t = 0$. A visual inspection of these event studies demonstrates fairly common pre-trends across treatment groups and confirms a relative lack of heterogeneity in the post-information period.

Taking this set of results in its entirety, I find limited evidence of information capitalization in the year following the EPA's lead NAAQS revision. If a price effect does exist, it appears to be economically small.

4.3 Event 2: 2010 revision to airport lead monitoring protocols

Following establishment of the new lead NAAQS standard, an initial mandatory monitoring scheme was put into place. This scheme required facilities with at least 1 ton per year (tpy) of estimated lead emissions to participate in ambient monitoring. Naturally, not all parties were content: in early 2009, a group of four environmental nonprofit groups petitioned the EPA to reconsider this emission threshold, citing the final 2008 NAAQS rulemaking, which included discussion of potential for facilities with 0.5 tpy to exceed the NAAQS under a reasonable "worst-case scenario". After another round of research and reconsideration, with comments collected from interested parties and stakeholders, in December 2010, the EPA finalized a revision to the lead NAAQS monitoring requirements (75 FR 81126). As a compromise of sorts, the EPA's final decision set the monitoring threshold at 0.5 tpy for all industrial sources, and 1 tpy for all airports. In addition, to gather evidence on the potential for NAAQS violations at airports with less than 1 tpy of lead emissions, the finalized decision mandated the study of ambient lead levels at a set of airports with annual emissions greater than 0.5 tons. These airports were to be selected so as to ensure a variety of physical, geographic, and technical characteristics. In turn, this could shed light on whether certain airport attributes may lead to difficulty in maintaining compliance with the updated lead NAAQS.

I leverage this shift in monitoring policy as a second information release event. In a perfect information setting, the public should interpret this new rule as a sign of the EPA's concern for potential health risks near airports with lower absolute levels of emissions than previously acknowledged. Moreover, the discrete threshold set in this revision provides an interesting natural experiment. Airports below the monitoring threshold remain "safe" in terms of the NAAQS as they will not be monitored, while those above the threshold are eligible for monitoring and could eventually be found in violation.

As before, I run a baseline diff-in-diff analysis that considers distance-varying average capitalization of this new information across all airports. For this event, however, I supplement the analysis with a triple differences estimation that tests for heterogeneous price responses at airports above ($\text{Elig}_j = 1$) and below ($\text{Elig}_j = 0$) the newly established lead monitoring eligibility threshold of 0.5 tpy:[16]

$$\log(Price)_{ijst} = \beta_1 \text{Dist}_i + \beta_2 \text{Dist}_i \times \text{Elig}_j + \gamma_1 \text{Post}_t + \gamma_2 \text{Post}_t \times \text{Elig}_j + \gamma_3 \text{Post}_t \times \text{Dist}_i + \delta \text{Dist}_i \times \text{Post}_t \times \text{Elig}_j + \text{FE}_{\alpha,\tau,\eta} + \rho_j X_i + \varepsilon_{ijst} \tag{1.2}$$

Estimation results are presented in Table 2. In columns (1) and (2), I do not find any meaningful evidence of an average post-monitoring-revision effect. In column (2), my preferred specification, the point estimates imply an average discount of less than one percent for all homes closer than 3km, relative to the base post-info average of homes within 3-5km. A similar story holds for the triple difference models in columns (3) and (4): effect sizes are again relatively small, though noisy in this case due to limited statistical power. In results from column (4), my estimates imply (imprecisely) that becoming eligible for monitoring actually increases property prices for homes within 1km of an airport, relative to neighboring properties. Similarly to Section 4.1, I run a non-parametric event study analysis, and share the results in Figure 6. No systematic story emerges from this visual exercise, though for sales within 1km, it is clear that prices at eligible airports did not systematically decline. Overall, I take this set of results as moderate evidence that revisions to federal monitoring did not capitalize into housing prices via a risk awareness channel.

4.4 Event 3: Release of monitoring study results

The third information revelation event I study is the release of results from a mandatory ambient lead monitoring program at 17 of 55 US airports with emissions estimated to be above 0.5 tpy. Recall that this subset of airports was selected for monitoring in order to better understand whether and when airport facilities generate ambient concentrations comparable to industrial facilities of a similar emissions-based size. While limited research on ambient lead levels at airports had been undertaken previously, the consensus was that more data was needed. Findings from this study – namely the calculation of a 3-month rolling average ambient Pb concentration – would determine where monitoring should occur in the future. Summary statistics in Appendix Table A3 suggest the selection of airports into the study was quasi-random in observables, as chosen facilities vary immensely in geography, flight frequency, and estimated emission levels.

The EPA released their preliminary monitoring findings to the public in June 2013. The two policy revisions I used as information treatments in sections 4.1 and 4.2 had the ability to affect *perception* of health risk and likelihood of violation, but did not provide information on actual ambient air quality. The release of this monitoring information, however, allows an observer to directly determine whether the monitored airport is in compliance with the lead NAAQS or not.

The public results showed that two of the seventeen monitored airports were found to be in violation of the lead NAAQS: San Carlos Airport in San Mateo County, CA (0.33 $\mu g/m^3$) and

[16] Appendix Table A3 holds summary information for the roughly 50 airports that fell above the 0.5 tpy monitoring threshold based on the 2008 NEI.

McClellan-Palomar Airport in San Diego County, CA (0.17 μg/m^3).[17] Among the fifteen airports found to be in compliance, thirteen were found to have concentrations below 0.075μg/m^3, releasing them from future monitoring requirements under rules of the revised NAAQS.

Again, I use the release of this information to frame a diff-in-diff and triple difference analyses. In the triple difference model, I look for heterogeneous price responses to the monitoring results across four groups: (a) homes near airports with less than 0.5 tpy of lead emissions; (b) homes near airports that were not monitored, but did report estimated emissions of more than 0.5 tpy; (c) homes near airports that were monitored and found to be in compliance, and (d) homes near airports that were monitored and found to be in violation. I denote these groups with indicator variables Monitor_j:

$$\begin{aligned}\log(Price)_{ijst} = \beta_1\text{Dist}_i + \beta_2\text{Dist}_i \times \text{Monitor}_j + \gamma_1\text{Post}_t + \gamma_2\text{Post}_t \times \text{Monitor}_j + \\ \gamma_3\text{Post}_t \times \text{Dist}_i + \delta\text{Dist}_i \times \text{Post}_t \times \text{Monitor}_j + \text{FE}_{\alpha,\tau,\eta} + \rho_j X_i + \varepsilon_{ijst}\end{aligned} \tag{1.3}$$

The main parameter estimates for these regressions are displayed in Table 3 As expected, in columns (1) and (2), I find that these monitoring results had little impact on *average* prices near airports across the US. There is no statistically significant difference in prices for homes less than 3 kilometers away from airports, relative to the base group located 3-5 kilometers away. But this average effect masks meaningful heterogeneity. In columns (3) and (4), I find that prices near airports that are now found in violation of the federal NAAQS suffer declines that are statistically significant at the one percent level. While all homes (out to distances of 5km) near these offending airports see average prices fall in the post-result period, homes within one kilometer bear an additional discount on the order of roughly 10%. Notably, I find relatively little price impact for all homes near airports that were found to be in compliance with the NAAQS, regardless of distance. And high emission airports that were eligible for monitoring but did not receive it also show little price response following the results' public release.

To dig into this striking result for properties near NAAQS-violating airports more carefully, I turn to the associated event study graphic shown in Figure 7. Across the distance-based panels, the common trends assumption appears to hold. More notable, however, is the graphic in the top panel illustrating residual price trends for homes within 1km of an airport. For homes near violating airports, there is a dramatic downward shift in the residual price function after the monitoring results were released. This price shock downward is on the order of 30% for the first few months following the information event, and slowly tapers away, regaining previous price levels about 6 months afterwards. This is consistent with a variety of previous results finding an initial "over-response" to information shocks in property markets, followed by an eventual return to local norms (Figlio and Lucas, 2004; Hansen et al, 2006; Bin and Landry, 2013; McCoy and Walsh, 2018; Garnache, 2020). In this context, the return to norm occurred in relatively short order, possibly following push-back regarding technicalities of the EPA's monitoring procedures, which were raised

[17] Program's information release (EPA, 2013) here.

quickly by both airports found to be in violation.[18]. In any case, the statistically-significant price responses to this information release suggests potential local lead risk became salient to homebuyers upon a monitoring violation, at least in the short run.

4.5 Event 4: Local lead risk disclosure following litigation settlement

The fourth and final information disclosure event I study was smaller in geographic scale, and targeted at a number of general aviation airports in the state of California. As such, in this subsection, I restrict my analysis only to the 129 airports located in this state.

The context behind this information disclosure event originates in a legal battle between an environmental non-profit group – the Center for Environmental Health (CEH) – and a group of airports and avgas distributers. This litigation began in 2011 when CEH alleged that the group of defendants were violating CA Proposition 65, a law that "requires businesses to provide warnings to Californians about significant exposures to chemicals that cause cancer, birth defects or other reproductive harm." The legal proceedings played out in courts for several years, and in December 2014, the case settled with a consent judgment against the defendants.[19] Of key interest in my context is injunctive relief that was specified in the settlement. The 23 California airports included as defendents were required (a) to display small, 2-foot-by-2-foot warning signs in areas accessible to the general public, and (b) mail a one-time disclosure letter, including explicit language warning about lead exposure, to all residences within 1 kilometer of the airport's border.[20]

The outcome of this settlement (lead risk disclosures to local residents and the general public) sets up a nice opportunity for another natural experiment. I construct diff-in-diff and triple difference analyses during the year before and after the information disclosures mandated by the consent judgment. Once again, the diff-in-diff considers distance bins as separate information treatment groups for all CA airports, while the triple difference analyses also incorporate variation across airports that were or were not parties to disclosures resulting from the consent judgment:

$$\begin{aligned}\log(Price)_{ijst} = \beta_1 \text{Dist}_i + \beta_2 \text{Dist}_i \times \text{Disclose}_j + \gamma_1 \text{Post}_t + \gamma_2 \text{Post}_t \times \text{Disclose}_j + \\ \gamma_3 \text{Post}_t \times \text{Dist}_i + \delta \text{Dist}_i \times \text{Post}_t \times \text{Disclose}_j + \text{FE}_{\alpha,\tau,\eta} + \rho_j X_i + \varepsilon_{ijst}\end{aligned} \tag{1.4}$$

I measure disclosure treatment (Disclose_j) in two different ways for my triple difference regressions. The simplest measure is an indicator for whether a transaction occurred at an airport where signs and local disclosure letters were mandated. I also use an alternative measure that incorporates intensity of local lead emissions. This results the following set of airport-specific indicators: those not in the settlement with low annual lead emissions (< 0.5 tons), those not in the settlement with high annual emissions (0.5 tons), those included in the settlement with low emissions, and those included in the settlement with high emissions. This more complex alternative set of indicators

[18] See an October 2013 alternative airport monitoring report by the San Diego Air Pollution Control District finding far lower ambient levels here. See the San Carlos Airport Pilots Association's memo of a similar nature here.

[19] Court proceedings occurred in Alameda County, CA; the final consent judgment can be obtained from their website under case number RG-11-600721.

[20] Airports included in the judgment are listed in Appendix Table A4.

allows for price responses to disclosure letters and signage to vary by actual intensity of localized pollution.

Results are presented in Table 4. All models in this table include controls for housing structure characteristics. In column (1), I again find that there is no average price effect across all CA airports following the lawsuit's resolution. Indeed, this is what we would expect: mandated disclosures only occurred at one fifth of state's general aviation facilities. In columns (2) and (3), I present results from the triple difference analyses, looking more specifically for price reactions near airports where residents received information about their potential exposure to lead hazards. Interestingly, even these results find little evidence that this new information affected housing prices. Any price drop accruing to properties within 1km of an airport that provided local disclosure is small: point estimates are less than one percent and not statistically significant. Decomposing this further in column (3), there is also no evidence of an effect at airports where disclosure occurred and emission levels are high.[21]

Overall, I find little evidence that this litigation-generated disclosure mandate affected local housing prices. This is an interesting result in contrast to previous findings that show environmental information disclosure is an effective driver of housing prices (Pope, 2008a; Pope, 2008b; Frondel, 2020). The nuance in this case could be that disclosure was a one time event: current residents directly received information about the hazard, but do not have incentive to forward this information to future buyers. Such a story would align with the information asymmetry narrative that motivates the aforementioned literature on property-level disclosure. Moreover, my results accord with previous research demonstrating that warnings related to Proposition 65 are often ignored by California consumers, perhaps due to conditioning from the sheer abundance of product warnings related to this law (Robinson et al, 2019).

4.6 What can be said about longer term price trends?

As a supplemental analysis, in this subsection I summarize airport-level price evolutions over the entire 2008-2015 period. While my quasi-experimental empirical designs in sections 4.1-4.4 were based on short-run price responses to new information, it is possible that information about airborne lead risk accumulated in the public's mind over the entire period, resulting in a slow, longer-run price decline for properties in immediate proximity to airports. Using a slightly modified empirical approach, I investigate this potential channel here.

I estimate models of a hedonic nature, using all data from the period 2008-2015.[22] I estimate a linear regression of the form

$$\log(Price)_{ijt} = \alpha_j + \beta_j \text{Dist}_i + \gamma_j \text{Dist}_i \times t + \tau_t + \rho_j X_i + \varepsilon_{ijt} \tag{2}$$

[21] In Figure 8, I plot the event study analogue to the column (3) results. Results are noisy, but confirm a flat price trajectory for sales of homes within 1km of airports included in the settlement.

[22] For completeness: my estimation sample here consists of all transactions (1) where housing structure characteristics are available and (2) at airports with >100 observations over the time period and at least 5 sales occurring in all 3 distance bins.

and am interested in the resulting distribution of parameter estimates β_j and γ_j. Note that I estimate separate hedonic price functions (β_j, γ_j, ρ_j) for each airport, but include homogeneous year and month fixed effects that capture temporal patterns assumed uniform across all housing markets in the US. Sales prices are adjusted for annual inflation using a national CPI.

These regressions result in a set of airport-level, *initial* distance-bin differentials β_j. These estimates capture average log-price differences for (year) 2008 transactions on properties <1km or 1-3km from an airport, relative to the base level for properties at a 3-5km distance. Results from Sections 4.1-4.4 generally confirm that properties at closer distances to a neighboring airport sell at a relative discount, so I expect the distribution of my β_j estimates to tell a similar story.

Similarly, γ_j is a set of estimates describing differential time trends by distance bin at each airport. γ_j can be roughly interpreted as an annual percent deviation for properties <1km or 1-3km from a given airport, relative to the base group's annual trend. In this case, forming a prior on the mean and shape of the resulting estimates' distribution is less straightforward. If information about potential lead exposure and associated health risks near general aviation airports has worked its way into public knowledge, then annual price trends in the immediate vicinity of airports could be relatively diminished compared to those further away.

The resulting distributions of β_j and γ_j estimates are visualized in Figure 9. In Panel (a), the density plots for $\widehat{\beta_j}$ are normal in shape, with a median value of -0.036 for transactions within 1km of an airport and a median value of -0.016 for transactions 1-3 km from an airport. These results are consistent with my previous results, though the visualization of the distribution makes clear there is some heterogeneity across airports. In Panel (b), I show the analogous density plots for $\widehat{\gamma_j}$. Interestingly, I find the median trend estimate to be close to zero for both distance groups. This result does not lend much support to the notion that the general public became increasingly aware of potential lead risks near general aviation airports over the studied time period.

I take the latter result one step further, however, and examine whether several factors may be driving this price trend heterogeneity. I estimate a simple descriptive regression of the form:

$$\begin{aligned}\widehat{\gamma_j} = \theta_0 + \theta_1(\Delta\text{Tot. FC})_j + &\theta_2(\Delta\text{PEA FC})_j + \theta_3(\Delta\text{Pb emissions})_j + \\ &\theta_4(\text{Monitored}_j) + \theta_5(\text{CEH airport}_j) + \varepsilon_j\end{aligned} \tag{3}$$

θ_1 and θ_2 describe the relationship between $\widehat{\gamma_j}$ and the percentage change in total flights and PEA flights, respectively, at airport j from 2008 to 2015. θ_3 describes its correlation with the percent change in lead emissions at airport j reported from 2008 to 2014. θ_4 and θ_5 are coefficients on indicator variables: the former for airports that received EPA lead monitoring in 2013, and the latter for airports that were parties to CEH's Proposition 65 litigation.

Results from this decomposition exercise are in Table 5. In column (1), I find little statistically significant evidence that any of the aforementioned factors are strongly correlated with the differential price trends for homes within 1km of an airport. Nevertheless, one estimate that does stand out is the value associated with airport monitoring. Despite the large standard errors, price declines over time for transactions within 1km of these particular airports are markedly stronger. This result is intriguing, as the associated release of monitoring results was the only information treatment that I found generated a robust price response. I compare this finding with those from Column (2), which examines differential price trends for homes 1-3km from the airport. None of these factors show any clear statistical relationship, with point estimates that are economically small as well. The overall conclusion I draw from this exercise is that any longer-run price responses to changes in local aviation traffic or estimated lead emissions did not vary much by distance. The factor that seems most likely to have contributed to longer-run differential price trends is airport-level air quality monitoring by the EPA.

5 Who lives by airports and does new information change this?

Taken as a whole, the results from Section 4 suggest that exposure to potentially dangerous levels of airborne lead pollution is concerning to homeowners, but that such information is rarely salient. As discussed more generally in recent theoretical work by Hausman and Stolper (2020), the incomplete information problem that exists in this context may present an especially pernicious market failure. If there is household-level, income-based residential sorting towards or away from airports based on noise – an obvious disamenity in neighboring areas that is highly correlated with aviation-generated air pollution – then lower-income households may suffer greater welfare losses from the hidden air toxicity.[23] Indeed, previous social science research has confirmed a robust correlation between lower socioeconomic status and increased residential exposure to aviation noise; see Collins et al (2020) and Sobotta et al (2007) for overviews.

To better understand who is most affected by airport-generated lead pollution, I investigate two environmental justice hypotheses in this section. First, I analyze correlations in neighborhood-level demographics around airports during the limited information period of 2009-2013, searching for evidence of disproportionate exposure to airport-generated lead pollution. Second, I test the "coming-to-the-nuisance" story by leveraging the EPA's 2013 monitoring results release as an information shock that could potentially shift neighborhood sorting patterns.

5.1 Disproportionate exposure

A recent EPA report studying potential avgas-generated lead exposure in the US estimates the national population count residing or attending schools within 500 meters of an airport at just under 5.2 millions individuals (EPA, 2020).[24] With census block level counts from the 2010 Census, they show in aggregate that proportions of racial minorities and children under five living or attending school within this radius are essentially identical to national averages.[25] This EPA report

[23]Given that lead is a highly toxic chemical that retards childhood social and behavioral development, hindered intergenerational mobility may be a natural ramification of the spatial equilibrium that results from the hidden pollution exposure.

[24]An earlier 2010 EPA analysis, using Census data from the year 2000, estimated that 16 million individuals reside and 3 million children attend school within a kilometer of an airport (75 FR 22440).

[25]For example: 7.0% of those living within 500m of an airport are under age 5, while 7.0% of the national population is under age 5; 20.2% of those in airport-proximity are non-white, while 27.6% of the national population

describes the racial and age composition of the population that is being exposed to airborne lead near airports, but in some sense, its findings could result from a ecological fallacy due to its reliance on national measures. In what follows, I describe a complementary analysis that uses a richer set of socio-demographic measures, relies on within-airport, distance-based measures of disproportionate exposure, and studies heterogeneity by flight frequency and wind direction. This alternative approach uses demographic measures from the 2009-2013 ACS at the census block group level - a slightly larger geographic scale. I focus on this time period as it covers the years directly prior to release of results from the EPA's airport monitoring program; in essence, I maintain a view of this period as one where households still have incomplete information about lead pollution levels at their local airport.

To study environmental justice correlations in this airport-centered context, I estimate regressions of the form:

$$Y_{ij} = \alpha_j + \beta \text{Dist}_{ij} + \varepsilon_{ij} \tag{4}$$

where i indexes block groups, j indexes airports, α_j is an airport fixed effect, Dist_{ij} is a set of distance-to-airport bins (< 1km, 1-3km, 3-5km), and ε_{ij} is an error term. Y_{ij}, the dependent variable in these regressions, is a set of block-group-level demographic measures: median income (logged), fraction of individuals with household income below 150% of the poverty line, fraction of adults with less than a high school education, fraction of black residents, fraction of Hispanic residents, fraction of residents in rented housing, median rent price (logged), median home price (logged), fraction of residents under 10 years old, and fraction of residents over 59 years old. The environmental justice literature has found disparate impacts along a number of dimensions, so I look for correlations in as broad of a sense as the data permits. By using within-airport variation to estimate my parameters of interest (those on the distance bins) I am asking a slightly different question than the EPA did in their 2020 analysis: are the demographics of block groups in immediate proximity to a given airport systematically different from those slightly further away? Again, Figure 3 provides a representative visual sense of the spatial scale I study.

Panel A of Table 6 contains results from these exploratory regressions. Note that each column-by-panel pair represents a separate regression, so this table summarizes coefficients from a total of 30 regressions. In line with results from the EPA's block-level analysis, these baseline regressions using within-airport demographic variation find relatively limited support for claims of environmental injustice. I do find that Hispanics, less-educated adults, and children make up a statistically larger fraction of the population in the immediate vicinity of airports, though the magnitudes of these differences is economically small (1.5%, 1.0% and 0.4%, respectively, relative to the baseline demographics at a distance of 3-5km.) I also find that older adults are less likely to live nearby, and reassuringly, that an increasing price gradient along distance bins confirms the pattern from my analysis with the Zillow data. I find no statistical evidence of distance-driven differences in measures related to income, rent, or the fraction of black population.

is non-white; 38% of students attending school within 500m of an airport are non-white, while 46.7% of students nationally are non-white.

In Panels B and C, I estimate similar correlative regressions, but incorporate interaction terms to allow for heterogeneity by flight counts and wind direction. In Panel B, I allow parameters on the distance bins to vary by airport based on whether its PEA flight count in 2009-2013 was above or below the national median. This analysis accentuates findings from Panel A: any statistically significant evidence of potential environmental injustice remains economically small and is occurring largely at airport facilities with higher levels of PEA traffic.

Finally, in Panel C, I look for differential correlations based on whether or not a block group receives wind coming from the direction of a nearby airport more than 30% of the time.[26] Being most frequently downwind of airports, residents in these block groups will bear the heaviest brunt of local pollution exposure. Results from this model are striking: block groups within 1km of an airport that receive heavy wind have 9% lower median incomes and have a roughly 3% higher black population than less wind-frequent block groups in the same distance category. Furthermore, though the differences are smaller and not statistically significant, similar patterns hold for measures including the fraction of the population that is Hispanic, the population fraction living under 150% of the poverty line, population fraction with less than a high school education, as well as the fraction living in rented housing and the median rental price.

The regression results in this panel do raise potential environmental justice concerns: after simply accounting for wind's ability to deliver pollution unevenly over space, there is some evidence that lower income and minority populations are burdened with relatively higher lead pollution from airports. This finding is consistent with work in other contexts that has highlighted the importance of using wind patterns to delineate true exposure (Grainger and Ruangmas, 2018; Hernandez-Cortes and Meng, 2020). It also accords with Stolper and Hausman's information and EJ narrative. Since runways are directionally sited based on prevailing wind patterns and airport noise is heaviest directly under flightpaths, the results in Panel C suggest that an environmentally unjust outcome on the margin of air pollution exposure could be resulting from sorting due to noise.

5.2 Coming to the nuisance

Next, I turn to an investigation of whether and how neighborhoods changed following the information disclosure rendered by the mid-2013 release of EPA airport lead monitoring results. In Section 4.3, I found that local property markets did capitalize information about ambient air quality violations reported during this release; though this price effect was short-term, I explore in this section whether the new information about local air quality resulted in any longer-run shifts in local demographic characteristics.

The econometric model I estimate is a parsimonious long-difference analogue of Equation (4):

$$\Delta Y_{ij} = \alpha_j + \beta \text{Dist}_{ij} + \varepsilon_{ij} \tag{5}$$

[26] A block group that receives wind 30% of the time is at approximately the 90th percentile of all block groups in terms of wind frequency.

Here, $\Delta Y_{ij} \equiv Y_{ij,2018} - Y_{ij,2013}$, so this regression's dependent variable is the change in a block group's demographic characteristics from the 2009-2013 ACS sample to the 2014-2018 ACS sample. I am interested in the coefficients, β, looking for potentially differential changes by distance-to-airport bin. Again, these regressions include airport fixed effects, so the variation used to identify β comes from distance-based differences in demographic change within a given airport. Given the larger scope for potential confounding factors in a regression studying longer-run change, I characterize these coefficient estimates as descriptive rather than causal.

Estimation results from regressions of the form described in Equation (5) are presented in Panel A of Table 7. As perhaps expected, these results do not illustrate any meaningful differences in average demographic changes across distance bins. But I do expect there to be meaningful heterogeneity hiding behind these baseline, average results. I attempt to tease it out in two ways. First, in Panel B, I again interact the distance bins with an indicator for block groups that receive wind more than 30% of the time from the direction of the nearest airport. These results also show essentially null effects across demographic indicators: block groups strongly downwind of airports do not demonstrate significantly different sorting patterns.

Finally, in Panel C, I interact the distance bins with the set of airport-level monitoring indicators from Equation (1.3): ineligible and unmonitored, eligible and unmonitored, monitored and found in compliance, or monitored and found in violation. This regression should provide the clearest insight into whether nuisance-based sorting occurred after airport-specific information was shared with the public. In particular, since I found a short-run sales price effect at airports in violation of the NAAQS, it seems that information about lead risks was most salient in those two locales. Before reporting results, a caveat is in order: a total of only 5 block groups fall within one kilometer of the two airports that were found to be in violation during monitoring. As such, a small sample disclaimer must apply to this subset of estimates.

The key statistically significant results imply the following: a relative decline (2.3%) in the fraction of the local population under age 10 living within 1km of airports found in violation; sizable changes in the renter/owner composition of these neighborhoods in the immediate vicinity of violations; and large shifts in these neighborhoods' racial and ethnic compositions. Moreover, the sign and magnitude of point estimates on neighborhood income and poverty rates also imply sizable sociodemographic shifts, though they do not meet conventional levels of statistical significance. It would be naive to claim these demographic shifts result purely from the information shock provided by airport, but this set of results does accord with my broader findings: if air quality violations following EPA monitoring makes local lead risk salient to housing markets, temporarily driving down local sales prices, this could be an initial source of the local population evolution I observe in the ACS block group level data. While the results in Panel C should be viewed as suggestive in nature rather than definitive, there does seem to be a sociodemographic response consistent with the "coming to the nuisance" narrative.[27]

[27] Even if I had a larger sample of block groups falling within one kilometer of the two airports found to have NAAQS violations, it is impossible to explicitly diagnose whether residential mobility hypotheses apply with this type of aggregate data. See Depro et al (2015) for related discussion.

6 Conclusion

This paper documents economic and sociodemographic responses to information shocks about potential lead exposure near hundreds of US general aviation airports. I estimate the causal impact of new air quality information on local housing prices, and find that ambient lead pollution is rarely salient to homebuyers. Several types of information about potential health risks from lead do not drive prices. However, when monitoring shows an airport to be in violation of the EPA's lead NAAQS, I do find a strong short run price decline for properties within 1km of the facility. I also study the demographic compositions of populations living in proximity to these airports, and how these compositions change with new information on potential lead exposure. I find that populations living within 1km and downwind of airports are relatively poorer than neighboring populations, with less education and a higher probability of being a racial or ethnic minority. Following the release of airport monitoring results in 2013, I also find suggestive evidence of demographic changes that are consistent with environmental sorting, including a reduction in children residing within 1km of airports found in violation.

These findings add a new context to the growing set of research exploring when environmental dis(amenities) are and are not salient to local residents. Moreover, the results largely align with and provide empirical support for a limited information channel acting as an underlying driver of environmental injustice. From a policy perspective, given the estimated benefits of a hypothetical reduction in lead from piston-engine aircraft traffic[28] and the potential for environmental sorting to be welfare improving in the absence of stricter regulation, my empirical findings highlight the importance of proactive monitoring and information disclosure when revising environmental policy - especially when a particular pollutant's levels or potential for health risk is not salient to consumers.

[28]Both Wolfe et al (2016) and Zahran et al (2017) value the potential human capital benefits on the order of $1 billion annually.

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Figures and Tables

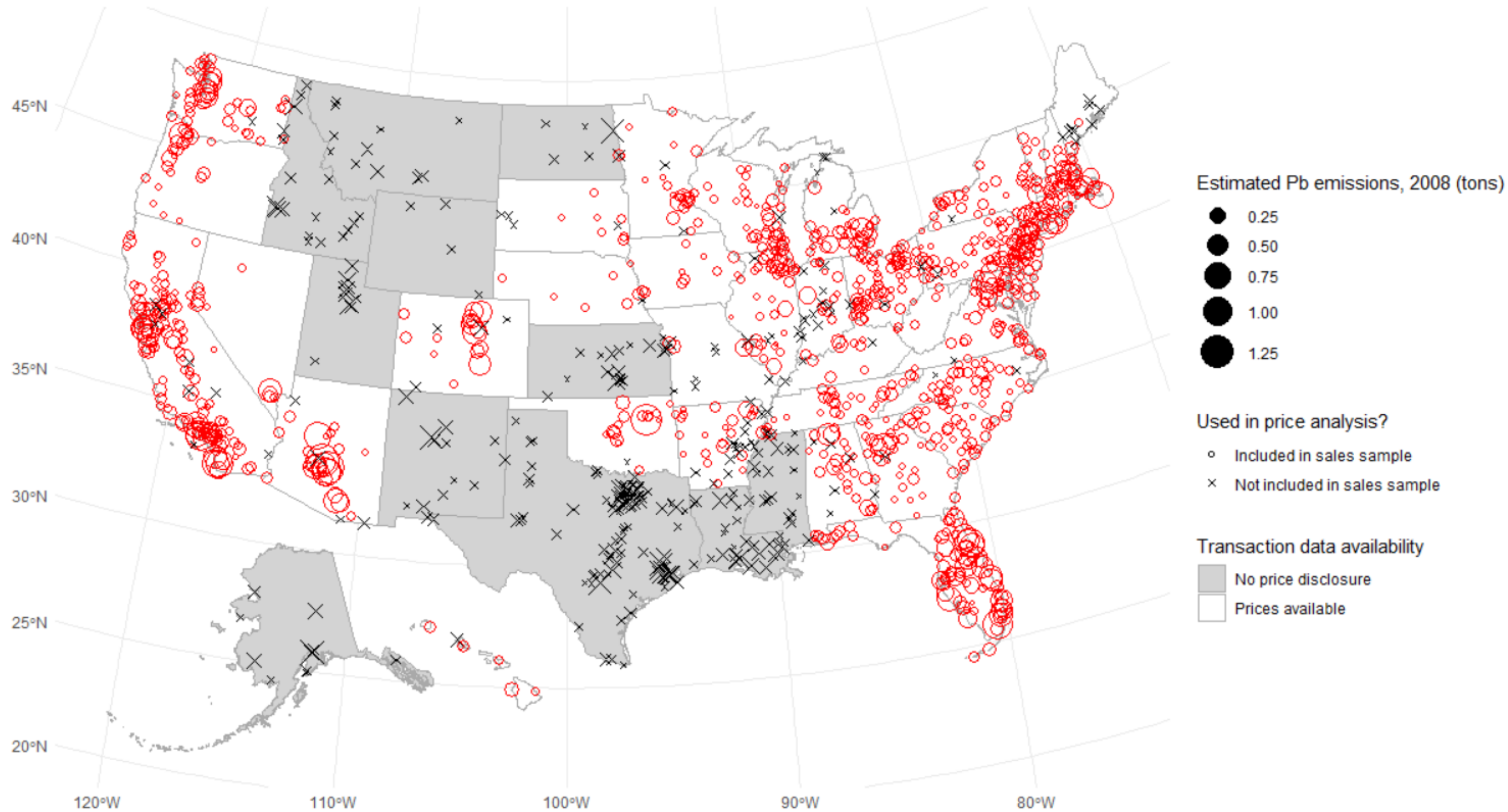


Figure 1: Map of US airports with estimated total Pb emissions greater than 0.5 tons in 2008; Red circles denote airports' whose housing markets are included in my analysis; black crosses denote those omitted due to data limitations.

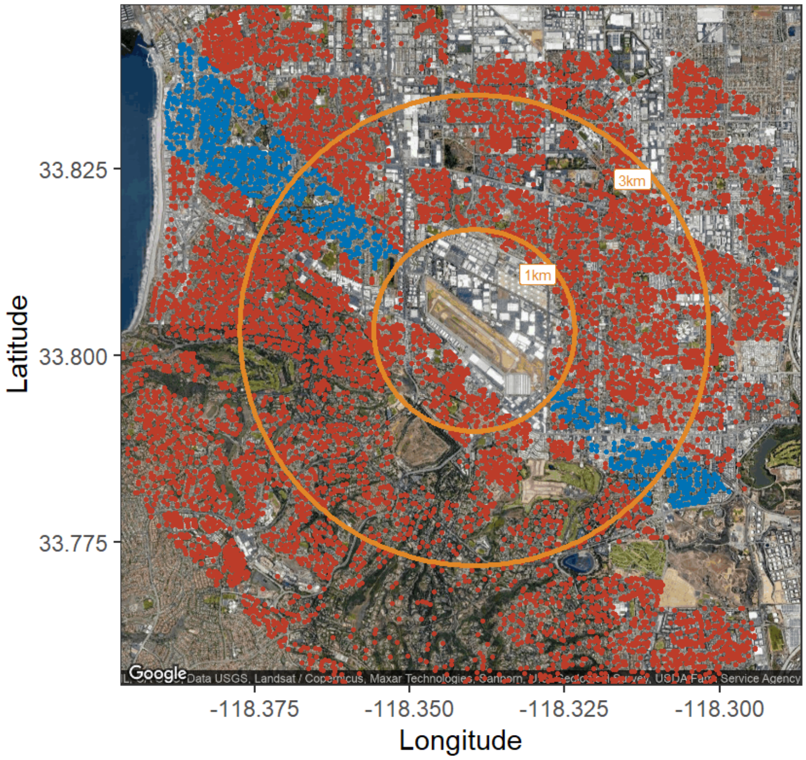


Figure 2: Representative airport-level property transaction sample: all qualifying sales transactions that occurred within 5 kilometers of Zamperini Field, in Los Angeles county, California.

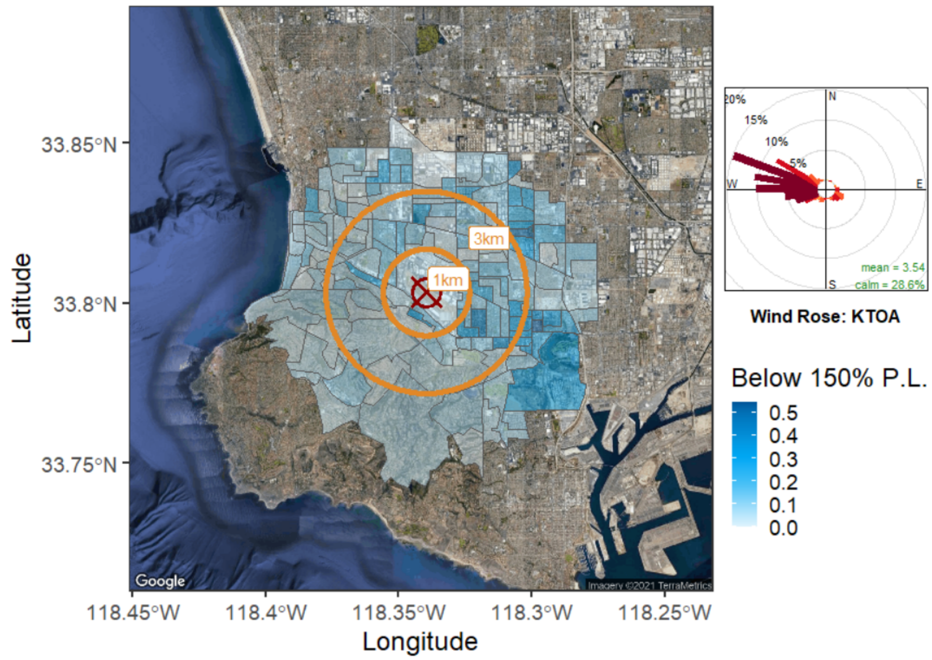


Figure 3: Main figure is a census block group map for Zamperini Field; visualized variable is the fraction of block group population that lives on a household income below 150% of the national poverty line. Subfigure is an airport wind rose based on 2006-2010 airport-generated meteorological reports.

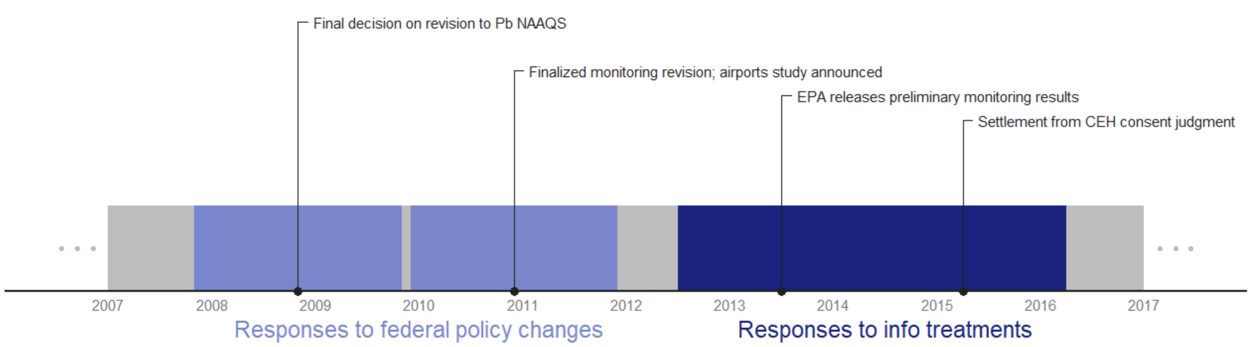


Figure 4: Event study timeline: four information releases from 2008-2015, with studies focused on one-year windows surrounding the event date. (Attribution: Figure adapted from R code by Ed Rubin.)

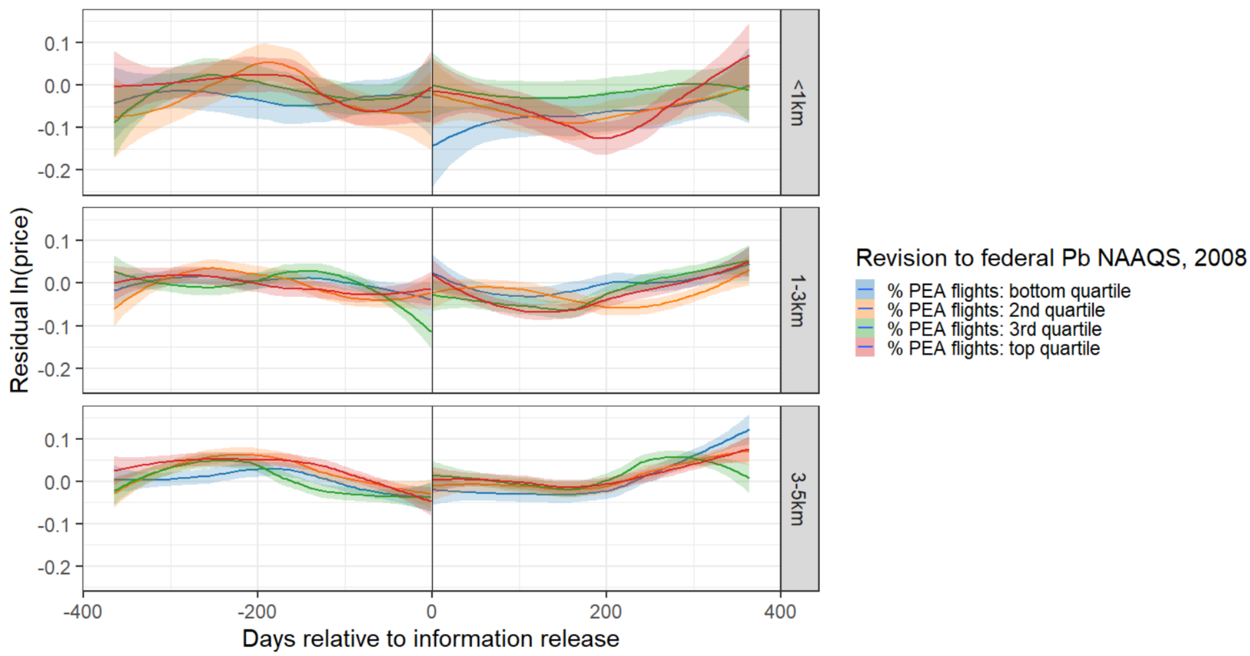


Figure 5: Event study, 2008 revision to lead NAAQS (Event 1). Bold line is local polynomial estimate of price residuals over time. Residual price is conditional on airport and month fixed effects, state-specific time trends, and housing structure controls. Confidence interval is shaded area around line.

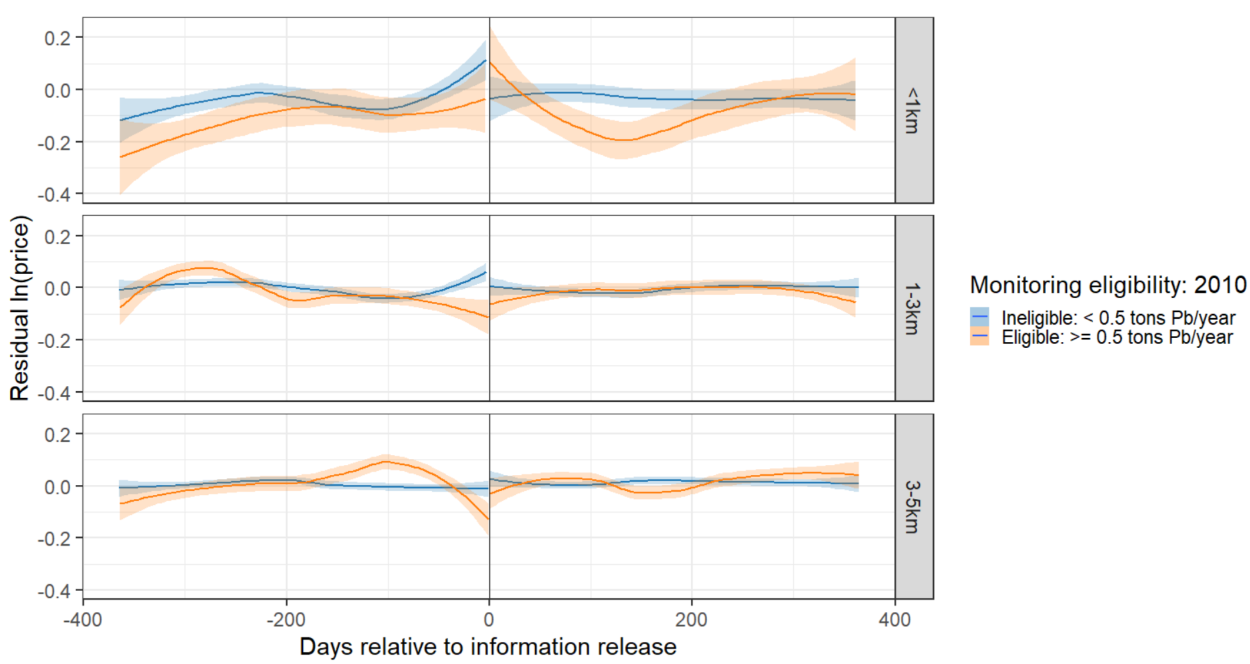


Figure 6: Event study, 2010 revision to airport monitoring protocols (Event 2). Bold line is local polynomial estimate of price residuals over time. Residual price is conditional on airport and month fixed effects, state-specific time trends, and housing structure controls. Confidence interval is shaded area around line.

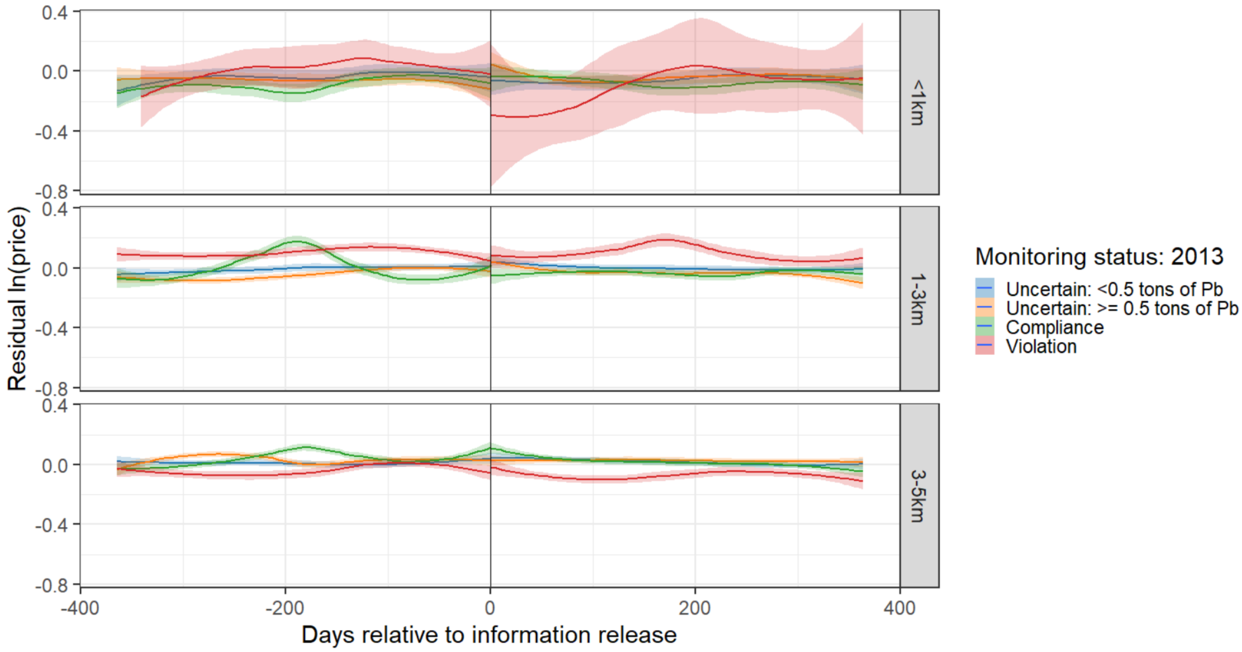


Figure 7: Event study, release of lead monitoring results (Event 3). Bold line is local polynomial estimate of price residuals over time. Residual price is conditional on airport and month fixed effects, state-specific time trends, and housing structure controls. Confidence interval is shaded area around line.

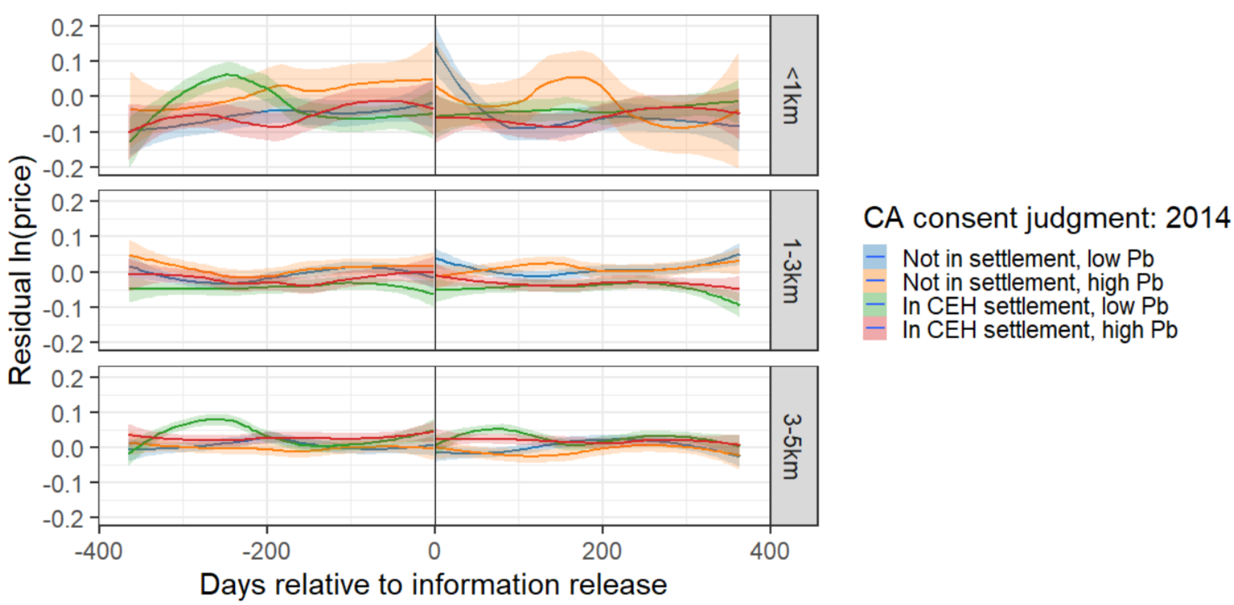
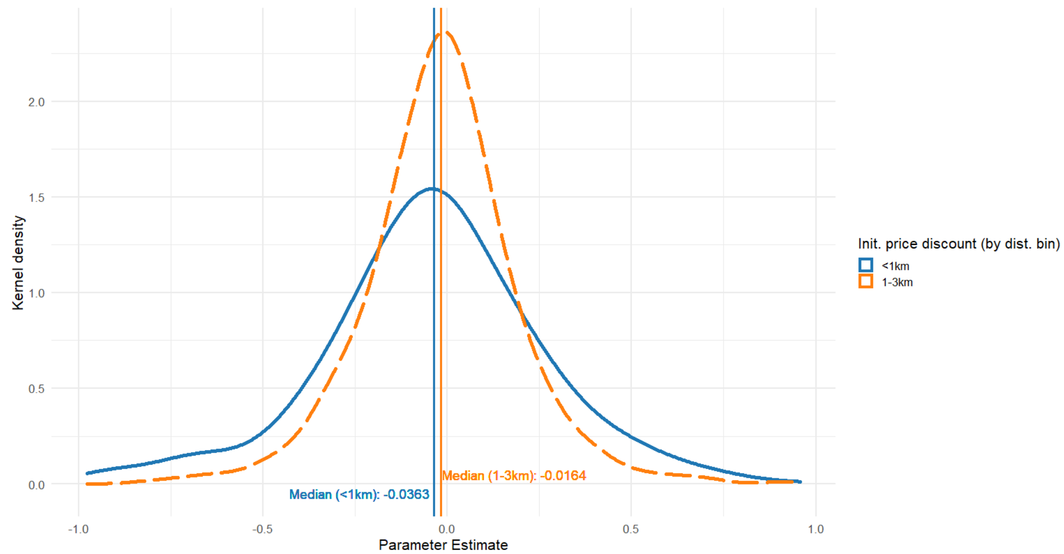
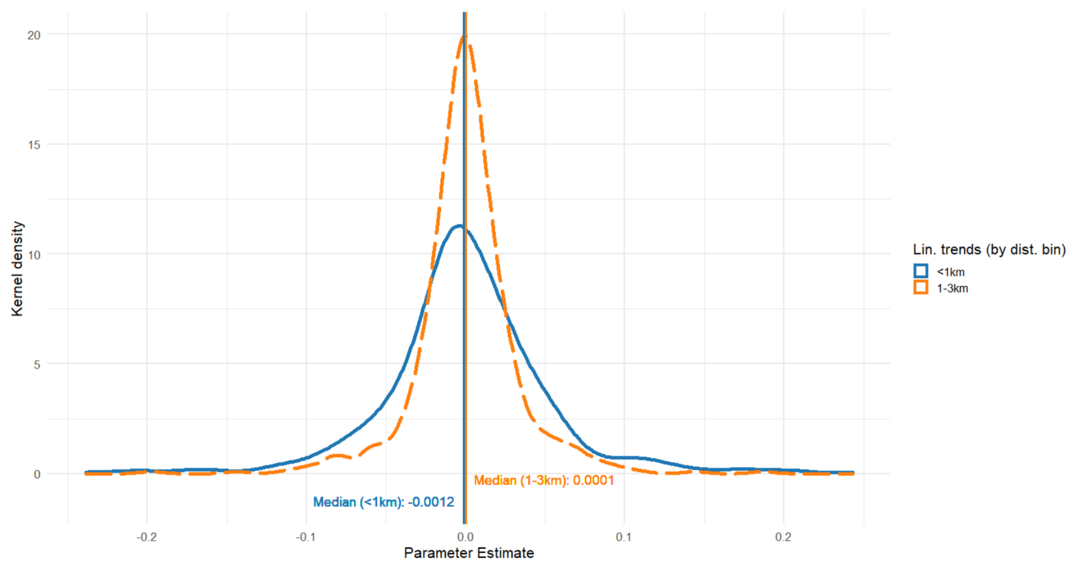


Figure 8: Event study, post-consent judgment information disclosure (Event 4). Bold line is local polynomial estimate of price residuals over time. Residual price is conditional on airport and month fixed effects, state-specific time trends, and housing structure controls. Confidence interval is shaded area around line.



(a) Distribution of airport-level initial price difference parameters (β_j) by distance bin.



(b) Distribution of airport-level time trend parameters (γ_j) by distance bin.

Figure 9: Summary of key parameter results (β_j, γ_j) from estimation of equation 1.5. Base distance bin is 3-5km; estimates presented are relative to these base levels and trends.

Dependent Variable:	log(Sale Price)			
	(1)	(2)	(3)	(4)
Dist: <1km	-0.062***	-0.040***	-0.092***	-0.052**
	(0.015)	(0.012)	(0.029)	(0.025)
Dist: 1-3km	-0.021**	-0.018**	-0.024	-0.007
	(0.009)	(0.008)	(0.016)	(0.014)
Post	-0.061***	-0.058***	-0.073***	-0.104***
	(0.010)	(0.010)	(0.018)	(0.019)
Dist: <1km × Post	-0.014	-0.028**	-0.008	-0.026
	(0.013)	(0.013)	(0.026)	(0.024)
Dist: 1-3km × Post	-0.009	-0.014	-0.002	-0.001
	(0.009)	(0.009)	(0.016)	(0.019)
% PEA flights: 2nd quartile × Post			0.027	0.004
			(0.027)	(0.027)
% PEA flights: 3rd quartile × Post			0.017	0.012
			(0.023)	(0.022)
% PEA flights: top quartile × Post			0.010	-0.002
			(0.021)	(0.022)
Dist: <1km × % PEA flights: 2nd quartile × Post			-0.021	-0.014
			(0.039)	(0.038)
Dist: 1-3km × % PEA flights: 2nd quartile × Post			-0.017	-0.027
			(0.027)	(0.026)
Dist: <1km × % PEA flights: 3rd quartile × Post			-0.001	0.007
			(0.035)	(0.029)
Dist: 1-3km × % PEA flights: 3rd quartile × Post			0.006	-0.018
			(0.025)	(0.023)
Dist: <1km × % PEA flights: top quartile × Post			-0.003	-0.003
			(0.035)	(0.031)
Dist: 1-3km × % PEA flights: top quartile × Post			-0.020	-0.015
			(0.021)	(0.023)
Fixed-effects:				
Month	Yes	Yes	Yes	Yes
Airport	Yes	Yes	Yes	Yes
Varying Slopes:				
State: time trends	Yes	Yes	Yes	Yes
Airport: housing structure chars		Yes		Yes
Regression details:				
Airports (clusters)	1,049	763	1,049	763
Observations	1,088,674	632,800	1,088,674	632,800
Adjusted R^2	0.4196	0.6398	0.4197	0.6399

Standard-errors are cluster-robust at airport level.
Base group for distance indicators is 3-5km. Base group for % PEA flights is the bottom quartile.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 1: Diff-in-diff results, 2008 revision to lead NAAQS.

Dependent Variable:	log(Sale Price)			
	(1)	(2)	(3)	(4)
Dist: <1km	-0.071***	-0.056***	-0.069***	-0.053***
	(0.023)	(0.018)	(0.024)	(0.018)
Dist: 1-3km	-0.025**	-0.018*	-0.025**	-0.018*
	(0.012)	(0.010)	(0.012)	(0.010)
Post	-0.049	-0.031	-0.049	-0.061***
	(0.033)	(0.042)	(0.033)	(0.016)
Dist: <1km × Post	-0.014	-0.008	-0.014	-0.009
	(0.021)	(0.017)	(0.022)	(0.018)
Dist: 1-3km × Post	-0.008	-0.008	-0.009	-0.008
	(0.011)	(0.009)	(0.011)	(0.010)
Eligible for monitoring study × Post			-0.0004	0.004
			(0.029)	(0.029)
Dist: <1km × Eligible for monitoring study × Post			0.017	0.037
			(0.055)	(0.055)
Dist: 1-3km × Eligible for monitoring study × Post			0.021	-0.003
			(0.026)	(0.014)
Fixed-effects				
Month	Yes	Yes	Yes	Yes
Airport	Yes	Yes	Yes	Yes
Varying Slopes:				
State: time trends	Yes	Yes	Yes	Yes
Airport: housing structure chars		Yes		Yes
Regression details:				
Airports (clusters)	1,059	776	1,059	776
Observations	1,074,157	630,596	1,074,157	630,596
Adjusted R^2	0.3895	0.6372	0.3896	0.6366

Standard-errors are cluster-robust at airport level.
Base group for distance indicators is 3-5km.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Diff-in-diff results, 2010 revision to airport monitoring protocols.

Dependent Variable:	log(Sale Price)			
	(1)	(2)	(3)	(4)
Dist: <1km	-0.100***	-0.065***	-0.087***	-0.058***
	(0.021)	(0.016)	(0.022)	(0.017)
Dist: 1-3km	-0.042***	-0.033***	-0.032***	-0.029***
	(0.012)	(0.010)	(0.012)	(0.010)
Post	0.005	0.011	0.007	0.012
	(0.014)	(0.013)	(0.014)	(0.013)
Dist: <1km × Post	0.008	0.009	0.002	0.006
	(0.012)	(0.011)	(0.014)	(0.012)
Dist: 1-3km × Post	0.005	0.008	0.002	0.009
	(0.008)	(0.007)	(0.008)	(0.007)
Unmonitored, >= 0.5 tons Pb × Post			-0.010	-0.004
			(0.021)	(0.021)
Monitored: compliant × Post			-0.006	-0.009
			(0.031)	(0.034)
Monitored: violation × Post			-0.061***	-0.038***
			(0.011)	(0.010)
Dist: <1km × Unmonitored, >= 0.5 tons Pb × Post			0.052	0.015
			(0.043)	(0.024)
Dist: 1-3km × Unmonitored, >= 0.5 tons Pb × Post			0.033	0.003
			(0.020)	(0.021)
Dist: <1km × Monitored: compliant × Post			0.026	0.015
			(0.035)	(0.034)
Dist: 1-3km × Monitored: compliant × Post			-0.009	-0.017
			(0.060)	(0.062)
Dist: <1km × Monitored: violation × Post			-0.095**	-0.097***
			(0.044)	(0.035)
Dist: 1-3km × Monitored: violation × Post			0.011	0.012
			(0.009)	(0.008)
Fixed-effects				
Month	Yes	Yes	Yes	Yes
Airport	Yes	Yes	Yes	Yes
Varying Slopes:				
State: time trends	Yes	Yes	Yes	Yes
Airport: housing structure chars		Yes		Yes
Regression details:				
Airports (clusters)	1,067	786	1,067	786
Observations	1,223,585	710,953	1,223,585	710,953
Adjusted R^2	0.4151	0.6474	0.4153	0.6475

Standard-errors are cluster-robust at airport level.
Base group for distance indicators is 3-5km. Base group for monitoring is unmonitored, < 0.5 tons of Pb.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Diff-in-diff results, release of lead monitoring results.

Dependent Variable:	log(Sale Price)		
	(1)	(2)	(3)
Dist: <1km	-0.072***	-0.069***	-0.076***
	(0.019)	(0.021)	(0.022)
Dist: 1-3km	-0.039***	-0.017	-0.021
	(0.014)	(0.017)	(0.019)
Post	-0.003	-0.0003	0.0007
	(0.022)	(0.021)	(0.022)
Dist: <1km × Post	-0.004	-0.001	-0.0004
	(0.014)	(0.022)	(0.024)
Dist: 1-3km × Post	0.011	0.017	0.018
	(0.009)	(0.013)	(0.014)
Included in CEH settlement × Post		-0.005	
		(0.016)	
Dist: <1km × Included in CEH settlement × Post		-0.007	
		(0.024)	
Dist: 1-3km × Included in CEH settlement × Post		-0.017	
		(0.015)	
Not in settlement, >=0.5 tons Pb annually × Post			-0.008
			(0.015)
In CEH settlement, <0.5 tons Pb annually × Post			-0.006
			(0.026)
In CEH settlement, >=0.5 tons Pb annually × Post			-0.006
			(0.014)
Dist: <1km × Not in settlement, >=0.5 tons Pb annually × Post			-0.019
			(0.024)
Dist: 1-3km × Not in settlement, >=0.5 tons Pb annually × Post			-0.008
			(0.018)
Dist: <1km × In CEH settlement, <0.5 tons Pb annually × Post			-0.012
			(0.028)
Dist: 1-3km × In CEH settlement, <0.5 tons Pb annually × Post			-0.012
			(0.018)
Dist: <1km × In CEH settlement, >=0.5 tons Pb annually × Post			-0.002
			(0.027)
Dist: 1-3km × In CEH settlement, >=0.5 tons Pb annually × Post			-0.026
			(0.020)
Fixed-effects			
Month	Yes	Yes	Yes
Airport	Yes	Yes	Yes
Varying Slopes			
State: time trend	Yes	Yes	Yes
Airport: housing structure chars	Yes	Yes	Yes
Regression details			
Airports (clusters)	129	129	129
Observations	204,282	204,282	204,282
Adjusted R^2	0.6721	0.6724	0.6725

One-way (Airport) standard-errors in parentheses
Base group for distance indicators is 3-5km. Base for CEH is non-settlement, <0.5 tons Pb.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Diff-in-diff results, post-consent judgment information disclosure.

	Trend parameter (<1km) (1)	Trend parameter (1-3km) (2)
(Intercept)	0.0004	-0.0003
	(0.004)	(0.002)
% $\Delta_{2008,2015}$ total flight count	0.0002	0.0002*
	(0.0002)	(0.0001)
% $\Delta_{2008,2015}$ PEA flight count	-0.0002*	-0.0001
	(0.0001)	(9.5e-5)
% $\Delta_{2008,2014}$ Pb emissions	5.5e-6	-6.3e-6
	(7.9e-5)	(5.1e-5)
Monitored airport (0/1)	-0.058	-0.004
	(0.053)	(0.006)
CEH lawsuit airport (0/1)	-0.003	0.0007
	(0.008)	(0.004)
Observations	593	593
Adjusted R^2	0.01053	0.00691

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Decomposition of longer-run price trends – an examination of potential factors contributing to heterogeneity

Dependent variable:	(1) Income	(2) Pov. Line	(3) <HS educ.	(4) Black	(5) Hispanic	(6) Rent/Own	(7) Rent	(8) Price	(9) Age:<10	(10) Age:>59
Panel A: baseline										
Dist: 1-3km	-0.0009	-0.0008	0.003	-0.003	0.007*	0.002	-0.004	-0.010	0.003***	-0.005***
	(0.008)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.008)	(0.0009)	(0.002)
Dist: <1km	-0.012	-0.002	0.010**	-0.002	0.015**	0.005	-0.004	-0.066***	0.004***	-0.010***
	(0.013)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.007)	(0.015)	(0.002)	(0.003)
Airports included: 1001										
Observations	36,934	37,086	37,077	37,086	37,086	36,990	31,971	35,531	37,086	37,086
Adjusted R^2	0.352	0.222	0.333	0.534	0.613	0.169	0.463	0.628	0.108	0.187
Panel B: het. by flight counts										
Dist: 1-3km	-0.015	0.003	0.007	-0.004	0.002	0.008	-0.009	-0.020	0.003	-0.003
	(0.014)	(0.005)	(0.005)	(0.005)	(0.008)	(0.009)	(0.008)	(0.012)	(0.002)	(0.003)
Dist: <1km	-0.002	-0.005	0.006	-0.002	-0.006	-0.013	-0.012	-0.035*	0.002	0.003
	(0.019)	(0.006)	(0.007)	(0.010)	(0.010)	(0.012)	(0.014)	(0.020)	(0.003)	(0.005)
Dist: 1-3km × Heavy PEA traffic	0.018	-0.005	-0.005	0.0009	0.007	-0.007	0.008	0.013	0.0007	-0.003
	(0.017)	(0.005)	(0.006)	(0.007)	(0.010)	(0.010)	(0.010)	(0.015)	(0.002)	(0.003)
Dist: <1km × Heavy PEA traffic	-0.014	0.004	0.005	-0.0002	0.028**	0.024	0.010	-0.041	0.003	-0.017***
	(0.025)	(0.008)	(0.009)	(0.012)	(0.013)	(0.015)	(0.016)	(0.027)	(0.004)	(0.006)
Airports included: 1001										
Observations	36,934	37,086	37,077	37,086	37,086	36,990	31,971	35,531	37,086	37,086
Adjusted R^2	0.352	0.222	0.333	0.533	0.613	0.169	0.463	0.628	0.108	0.188
Panel C: het. by wind frequency										
Dist: 1-3km	-0.001	0.0001	0.005	-0.004	0.011**	0.004	-0.003	-0.009	0.004***	-0.005***
	(0.009)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.009)	(0.001)	(0.002)
Dist: <1km	-0.009	-0.002	0.010*	-0.004	0.020**	0.008	-0.006	-0.070***	0.004**	-0.011***
	(0.015)	(0.005)	(0.005)	(0.006)	(0.008)	(0.009)	(0.008)	(0.017)	(0.002)	(0.003)
>30% wind direction	0.019	-0.012	-0.006	-0.016	0.015	-0.008	-0.009	0.059	0.003	0.003
	(0.047)	(0.015)	(0.018)	(0.016)	(0.026)	(0.024)	(0.023)	(0.042)	(0.004)	(0.007)
Dist: 1-3km × >30% wind direction	-0.066*	0.016	0.0006	0.022*	-0.009	0.026	-0.017	-0.087**	-0.005	-0.003
	(0.038)	(0.011)	(0.013)	(0.012)	(0.017)	(0.024)	(0.021)	(0.039)	(0.004)	(0.008)
Dist: <1km × >30% wind direction	-0.123**	0.027	0.023	0.043**	-0.002	0.039	-0.048	-0.044	-0.004	0.010
	(0.059)	(0.018)	(0.020)	(0.020)	(0.028)	(0.034)	(0.035)	(0.055)	(0.008)	(0.014)
Airports included: 710										
Observations	30,495	30,627	30,618	30,627	30,627	30,544	26,612	29,228	30,627	30,627
Adjusted R^2	0.336	0.207	0.314	0.531	0.611	0.156	0.462	0.635	0.097	0.157

Notes: Observations are at census block-group level. Standard errors are clustered by airport, with airport FEs included in all specifications.
Description of dependent variables: (1) log(median income), (2) % living w/ income <150% poverty line, (3) % w/ less than HS education, (4) % Black residents, (5) % Hispanic residents, (6) % of residents renting housing, (7) log(median rent price), (8) log(median home price), (9) % of residents under 10 years old, (10) % of residents over 59 years old.
Description of independent variables: Base group for distance indicators is 3-5km. Heavy PEA indicates airports above the national median during the 2009-13 period. Wind direction indicates all block groups that receive wind in their compass octant more than 30% of the time.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Environmental justice in neighborhoods near US airports.

Dep. variable: ($\Delta_{2018,2013}$)	(1) Income	(2) Pov. Line	(3) <HS educ.	(4) Black	(5) Hispanic	(6) Rent/Own	(7) Rent	(8) Price	(9) Age:<10	(10) Age:>59
Panel A: baseline										
Dist: 1-3km	0.0003	-0.0001	-0.0009	0.001	-0.0006	0.0004	0.0001	-0.002	-0.0010	0.001
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.0008)	(0.0009)
Dist: <1km	-0.006	-0.0001	-0.002	-0.0010	0.003	0.001	-0.004	-0.001	-0.002*	0.001
	(0.006)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)	(0.001)	(0.002)
Airports included: 1001										
Observations	35,928	37,071	37,055	37,071	37,071	36,964	29,662	34,127	37,071	37,071
Adjusted R^2	0.022	0.005	0.009	0.002	0.008	0.009	0.046	0.253	-0.0007	0.003
Panel B: het. by wind direction										
Dist: 1-3km	-0.0001	0.0002	-0.001	0.002	-0.0010	0.0000	-0.003	-0.002	-0.001	0.001
	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.0009)	(0.001)
Dist: <1km	-0.010	-0.0001	-0.003	-0.0003	0.002	-0.0005	-0.004	-0.004	-0.003*	0.002
	(0.007)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.007)	(0.002)	(0.002)
Dist: 1-3km × >30% wind direction	-0.002	-0.013	0.004	-0.003	-0.007	-0.0009	-0.002	0.020	-0.002	0.009
	(0.020)	(0.008)	(0.005)	(0.005)	(0.009)	(0.009)	(0.014)	(0.020)	(0.004)	(0.006)
Dist: <1km × >30% wind direction	0.013	0.010	0.012	-0.010	0.001	0.006	0.011	-0.0004	0.010	-0.017*
	(0.030)	(0.015)	(0.010)	(0.010)	(0.012)	(0.016)	(0.021)	(0.025)	(0.007)	(0.009)
Airports included: 710										
Observations	29,624	30,613	30,597	30,613	30,613	30,520	24,727	28,012	30,613	30,613
Adjusted R^2	0.023	0.004	0.011	0.003	0.008	0.009	0.049	0.250	-0.0005	0.0009
Panel C: het. by info release										
Dist: 1-3km	0.0004	0.0001	-0.0006	0.0006	-0.0002	-0.0003	-0.0006	-0.0010	-0.0008	0.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.0009)	(0.0010)
Dist: <1km	-0.007	-0.0004	-0.002	-0.001	0.004	0.001	-0.004	-0.004	-0.003**	0.001
	(0.007)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)	(0.002)	(0.002)
Dist: 1-3km × Unmonitored, >=0.5 tons Pb	-0.0007	-0.0006	-0.003	0.003	0.0008	0.004	0.007	-0.005	-0.003	0.002
	(0.013)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.010)	(0.012)	(0.003)	(0.003)
Dist: <1km × Unmonitored, >=0.5 tons Pb	0.015	0.003	-0.003	0.002	-0.013	-0.010	0.001	0.013	0.005	0.006
	(0.025)	(0.015)	(0.010)	(0.008)	(0.009)	(0.008)	(0.023)	(0.021)	(0.005)	(0.008)
Dist: 1-3km × Monitored: violation	0.007	-0.0008	-0.009**	-0.001	-0.022***	0.005	0.060**	-0.012	-0.010	-0.004
	(0.074)	(0.004)	(0.004)	(0.003)	(0.001)	(0.009)	(0.027)	(0.017)	(0.011)	(0.003)
Dist: <1km × Monitored: violation	-0.082	0.031	0.007	0.070***	-0.089*	-0.062***	0.152	-0.051	-0.023***	0.026
	(0.086)	(0.041)	(0.060)	(0.019)	(0.048)	(0.006)	(0.145)	(0.060)	(0.007)	(0.025)
Dist: 1-3km × Monitored: compliant	-0.002	-0.005	-0.003	0.006	-0.011*	0.010	-0.0001	-0.010	0.002	-0.004
	(0.023)	(0.012)	(0.004)	(0.006)	(0.006)	(0.010)	(0.013)	(0.015)	(0.005)	(0.003)
Dist: <1km × Monitored: compliant	0.001	0.004	0.006	0.007	-0.006	0.020*	-0.005	0.038	0.013**	-0.007
	(0.029)	(0.019)	(0.008)	(0.008)	(0.012)	(0.011)	(0.024)	(0.041)	(0.006)	(0.007)
Airports included: 1001										
Observations	35,928	37,071	37,055	37,071	37,071	36,964	29,662	34,127	37,071	37,071
Adjusted R^2	0.022	0.005	0.008	0.002	0.008	0.009	0.045	0.253	-0.0007	0.002

Notes: Observations are at census block-group level. Standard errors are clustered by airport, with airport FEs included in all specifications.
Description of dependent variables: all are first-differences of 2014-18 & 2009-13 5-year ACS measures. (1) log(median income), (2) % living w/ income <150% poverty line, (3) % w/ less than HS education,(4) % Black residents, (5) % Hispanic residents, (6) % of residents renting housing, (7) log(median rent price), (8) log(median home price), (9) % of residents under 10 years old, (10) % of residents over 59 years old.
Description of independent variables: Base group for distance indicators is 3-5km. Wind direction indicates all block groups that receive wind in their compass octant more than 30% of the time. Base group for info treatment is unmonitored, < 0.5 tons Pb.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Neighborhood demographic changes following airport monitoring results.

Appendix

Variable	Mean	Std. Dev.	Minimum	Median	Maximum	Obs. Count
	Distance: 3000-5000m					
Sales Price	717150.42	618378.45	10000	562750	9263592	9916
Construction Year	1970.58	20.25	1891	1971	2016	9898
Total Bedrooms	3.03	1.02	1	3	8	9858
Total Baths	2.47	1.02	1	2	10	9895
Acreage	1.49	2.52	0.01	0.22	17.3	9916
Direct Flight-path (dummy)	0.12	0.33	0	0	1	9916
	Distance: 1000-3000m					
Sales Price	671187.27	447525.73	11000	579000	8550000	7569
Construction Year	1971.49	21.71	1908	1964	2016	7563
Total Bedrooms	3.04	0.94	1	3	7	7523
Total Baths	2.43	0.88	1	2	9	7562
Acreage	1.1	1.95	0.03	0.2	11.13	7569
Direct Flight-path (dummy)	0.11	0.31	0	0	1	7569
	Distance: <1000m					
Sales Price	602864.93	244572.23	35000	593000	2387772	1084
Construction Year	1966.2	20.24	1911	1963	2016	1083
Total Bedrooms	3.03	1.02	1	3	8	1083
Total Baths	2.33	0.92	1	2	8	1083
Acreage	0.75	1.77	0.05	0.15	7.49	1084
Direct Flight-path (dummy)	0.12	0.32	0	0	1	1084

Table A1: Summary statistics for sales transactions data (2007-2016). Observations include all properties located within 5km of Zamperini Field (TOA).

Variable	Mean	Std. Dev.	Minimum	Median	Maximum	Obs. Count
	Distance: 3000-5000m					
Median Income	86578.4	35938.2	28017	86042	207031	81
Frac. below 150% pov. line	0.11	0.11	0	0.07	0.5	81
Frac. less than H.S. educ.	0.1	0.12	0	0.05	0.43	81
Frac. Black	0.06	0.07	0	0.03	0.37	81
Frac. Hispanic	0.25	0.22	0	0.17	0.9	81
Frac. Renters	0.4	0.28	0	0.36	1	81
Median Rent	1489.33	395.52	578	1580	2001	67
Median Home Price	620079.84	250802.47	58000	636900	1000001	79
Frac. under age 10	0.12	0.05	0.02	0.11	0.27	81
Frac. over age 59	0.21	0.09	0.05	0.21	0.46	81
Population	1787.27	834.99	419	1668	3903	81
	Distance: 1000-3000m					
Median Income	85592.59	33137.28	30875	81354	168438	59
Frac. below 150% Pov. Line	0.12	0.12	0	0.09	0.54	59
Frac. less than H.S. educ.	0.11	0.12	0	0.07	0.64	59
Frac. Black	0.04	0.06	0	0.02	0.33	59
Frac. Hispanic	0.25	0.22	0	0.17	0.86	59
Frac. Renters	0.35	0.24	0	0.29	0.93	59
Median Rent	1478.81	396.59	567	1407	2001	53
Median Home Price	612810.61	206196.49	14600	620100	1000001	57
Frac. under age 10	0.12	0.05	0.02	0.11	0.23	59
Frac. over age 59	0.21	0.08	0.05	0.2	0.46	59
Population	1606.46	815.19	520	1332	3506	59
	Distance: <1000m					
Median Income	67298.46	17290.49	46250	65223	108804	13
Frac. below 150% Pov. Line	0.15	0.13	0.01	0.11	0.44	13
Frac. less than H.S. educ.	0.06	0.04	0.01	0.05	0.13	13
Frac. Black	0.02	0.02	0	0.02	0.07	13
Frac. Hispanic	0.2	0.17	0.05	0.13	0.57	13
Frac. Renters	0.51	0.21	0.17	0.54	0.89	13
Median Rent	1426.62	333.8	765	1359	2001	13
Median Home Price	554330.77	165911.49	208300	592000	763500	13
Frac. under age 10	0.12	0.07	0	0.11	0.23	13
Frac. over age 59	0.21	0.13	0.08	0.21	0.56	13
Population	1593.08	771.29	683	1259	3311	13

Table A2: Summary statistics for 2009-2013 ACS demographic data. Observations are block groups within 5km of Zamperini Field (TOA).

(1) FAA LID	(2) Name	(3) State	(4) Total flights ('07-'16)	(5) PEA flights ('07-'16)	(6) Pb Emissions ('08)	(7) Pb concentration ('13)	(8) Transactions w/in 5km
DVT	PHOENIX DEER VALLEY	AZ	99, 198	49, 586	1.317	0.04	3, 464
FFZ	FALCON FLD	AZ	49, 846	26, 708	1.213		3, 312
RVS	RICHARD LLOYD JONES JR	OK	140, 411	76, 713	1.174		2, 251
DAB	DAYTONA BEACH INTL	FL	309, 768	159, 831	1.093		3, 338
LGB	LONG BEACH/DAUGHERTY FIELD	CA	527, 267	97, 490	1.025		7, 790
TMB	MIAMI EXECUTIVE	FL	223, 973	116, 670	1.025		7, 674
CHD	CHANDLER MUNI	AZ	30, 809	16, 743	0.917		5, 267
PRC	ERNEST A LOVE FIELD	AZ	71, 428	25, 350	0.904		115
SEE	GILLESPIE FIELD	CA	69, 169	39, 656	0.900	0.07	5, 090
MYF	MONTGOMERY-GIBBS EXECUTIVE	CA	187, 693	107, 524	0.869		4, 112
VNY	VAN NUYS	CA	583, 073	115, 706	0.766	0.06	7, 216
ACK	NANTUCKET MEMORIAL	MA	446, 306	240, 568	0.756	0.01	37
APA	CENTENNIAL	CO	631, 380	88, 700	0.730	0.02	4, 859
SFB	ORLANDO SANFORD INTL	FL	397, 740	207, 041	0.716		2, 088
RYN	RYAN FIELD	AZ	15, 255	12, 291	0.714		794
SNA	JOHN WAYNE AIRPORT	CA	1, 393, 016	125, 848	0.712		5, 074
FIN	FLAGLER EXECUTIVE	FL	43, 186	31, 277	0.712		1, 054
EVB	NEW SMYRNA BEACH MUNI	FL	75, 722	63, 024	0.685		1, 920
HIO	PORTLAND-HILLSBORO	OR	212, 177	89, 650	0.677		2, 672
VNC	VENICE MUNI	FL	59, 634	35, 062	0.675		3, 512
PAO	PALO ALTO	CA	73, 380	58, 634	0.659		1, 901
IWA	PHOENIX-MESA GATEWAY	AZ	191, 611	35, 218	0.658	0.12	6, 536
BFI	BOEING FIELD/KING COUNTY INTL	WA	703, 142	177, 338	0.650		5, 275
HWO	NORTH PERRY	FL	41, 336	34, 593	0.634		10, 552
52F	NORTHWEST RGNL	TX	8, 892	8, 326	0.629		
LVK	LIVERMORE MUNI	CA	67, 523	33, 104	0.624		4, 344
VRB	VERO BEACH RGNL	FL	245, 204	155, 914	0.624		3, 626
MRI	MERRILL FIELD	AK	19, 433	8, 203	0.610	0.07	
S50	AUBURN MUNI	WA	12, 007	11, 253	0.605	0.06	2, 740
PDK	DEKALB-PEACHTREE	GA	724, 995	196, 141	0.597		5, 943
GFK	GRAND FORKS INTL	ND	353, 227	199, 052	0.597		
GYR	PHOENIX GOODYEAR	AZ	20, 563	8, 534	0.596		3, 084
CRQ	MCCLELLAN-PALOMAR	CA	309, 144	70, 306	0.595	0.17	4, 387
DWH	DAVID WAYNE HOOKS MEMORIAL	TX	205, 024	99, 858	0.589		
PTK	OAKLAND COUNTY INTL	MI	380, 881	88, 947	0.586	0.02	2, 781
VGT	NORTH LAS VEGAS	NV	142, 322	74, 517	0.584		10, 818
TOA	ZAMPERINI FIELD	CA	71, 107	56, 857	0.580		4, 895
LNA	PALM BEACH COUNTY PARK	FL	43, 891	38, 634	0.577		6, 666
ISM	KISSIMMEE GATEWAY	FL	179, 815	94, 556	0.564		3, 227
DMW	CARROLL COUNTY RGNL	MD	33, 581	16, 278	0.559		850
DCU	PRYOR FIELD RGNL	AL	30, 487	17, 207	0.550	0.01	26
SSF	STINSON MUNI	TX	38, 485	26, 520	0.542	0.03	
HWD	HAYWARD EXECUTIVE	CA	99, 178	41, 762	0.540		4, 673
GXY	GREELEY-WELD COUNTY	CO	24, 679	8, 513	0.535		387
PUB	PUEBLO MEMORIAL	CO	108, 128	18, 625	0.533		352
RHV	REID-HILLVIEW	CA	35, 196	30, 614	0.532	0.09	5, 403
SQL	SAN CARLOS	CA	98, 888	46, 375	0.530	0.33	3, 829
FRG	REPUBLIC	NY	257, 605	64, 920	0.527	0.01	2, 357
FPR	TREASURE COAST INTL	FL	210, 060	154, 004	0.526		1, 109
OMN	ORMOND BEACH MUNI	FL	50, 019	43, 739	0.526		1, 643
MLB	MELBOURNE INTL	FL	225, 719	121, 444	0.521		4, 435
MGJ	ORANGE COUNTY	NY	14, 502	12, 577	0.505		198
S43	HARVEY FIELD	WA	3, 899	3, 757	0.502	0.02	1, 075
AEG	DOUBLE EAGLE II	NM	26, 092	13, 589	0.500		
HWV	BROOKHAVEN	NY	11, 646	10, 378	0.498	0.03	994

Notes: Characteristic summaries of airports eligible for EPA's monitoring pilot program following Pb NAAQS revision.
Column descriptions: (4) Total flight operations during 2007-16 period. (FAA TFMS). (5) Piston-engine flight operations during 2007-16 period. (FAA's TFMS). (6) Estimated Pb emissions, 2008 (tons, EPA's NEI). (7) Monitored 3-hr average Pb concentration , 2013 (EPA). (8) Arms-length, price-recorded property transactions w/in 5km of airport during 2-year window surrounding monitoring info release, 2012-2014 (Zillow's ZTRAX).

Table A3: Airport summary statistics: all airports with estimated 2008 Pb emissions over 0.5 tons.

Name	County
Bob Hope Airport	Los Angeles
Brackett Field	Los Angeles
Brown Field Municpal Airport	San Diego
Buchanan Field	Contra Costa
Camarillo Airport	Ventura
El Monte Airport	Los Angeles
Fresno Yosemite International Airport	Fresno
Hayward Executive	Alameda
John Wayne Airport	Orange
Long Beach Airport	Los Angeles
Los Angeles International Airport	Los Angeles
Meadows Field	Kern
Montgomery Field	San Diego
Napa County Airport	Napa
Oakland International Airport	Alameda
Palo Alto Airport	Santa Clara
Reid-Hillview Airport	Santa Clara
Sacramento Executive Airport	Sacramento
San Luis Obispo County Regional Airport	San Luis Obispo
Santa Barbara Municipal Airport	Santa Barbara
Santa Monica Municipal Airport	Los Angeles
Van Nuys Airport	Los Angeles
Zamperini Field	Los Angeles

Table A4: Airports included as defendents in CEH avgas lawsuit.